The Allocation of Talent: Evidence from the Market of Economists

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Abstract Recent research in labor economics has highlighted the substantial and long-lasting adverse effect of recessions on employment prospects and earnings. In this paper, we study whether individuals react to these shocks by changing career paths, thereby affecting the distribution of talent between sectors. More concretely, we examine how publications and career choices of graduates from the leading US economics PhD programs vary with the state of the business cycle at time of application and at time of graduation. Our results strongly support the predictions of a Roy-style model of self-selection into sectors: we find that adverse macroeconomic conditions at time of application lead to a substantially more productive selection of individuals into academia and at time of graduation they lead to more PhDs deciding to stay in academia.

Keywords: Talent Allocation, PhD Economists, Roy Model, Business Cycle
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1 Introduction

There is a growing interest within labor economics in the effect of macroeconomic conditions on microeconomic outcomes. In particular, recent studies have found a substantial and persistent negative impact of recessions on individuals' employment and earnings.[1] Yet, to the best of our knowledge, there is no study which examines whether individuals react to these recession shocks in terms of occupational choice and the potential impact the reaction might have on talent allocation and productivity across sectors. Our paper fills this gap in the literature by looking at a specific market where individual skills can readily be measured—academia.

We study the impact of the business cycle on skill allocation in the academic labor market. This is done by relating the research productivity and career choice of (potential) economists graduating from the top 30 US universities to the change in the unemployment rate during the last 50 years. To guide our empirics, we develop a Roy-style model (1951) of the selection of talent between business and academia, where entering academia is competitive but attractive during recessions. This model predicts that fewer economists who faced a recession at time of application to the PhD program stay in academia after graduation. Those who do stay are positively selected on academic productivity. Moreover, if there is a recession at the time of graduation, more economists pursue academic employment, which leads to more publications per PhD graduate.

The results of the empirical analysis strongly support the theoretical predictions. In particular, they show that individuals do react to recession shocks. Economists applying or graduating during recessions publish significantly more than economists applying or graduating in a boom. A recession at entry leads to fewer PhD students staying in academia, a recession at graduation has the opposite effect. Moreover, the effects are of economically substantial magnitude. Taking our estimates literally, we expect assistant professors from the cohort of graduate students who applied for the PhD during the recession of 2008 (3.5 percentage points increase in unem-

[1] See, for example, Oreopoulos, Wachter, and Heisz (2008), Sullivan and von Wachter (2009), Kahn (2010), Kondo (2008), Oyer (2006), Oyer (2008).

ployment) to be around 24 percent more productive than assistant professors from a cohort applying in an average year (0 percent unemployment change). We also expect PhD graduates from 2008 to produce on average 20 percent more publications than economists graduating in an average year.

Our results contribute to several discussions in the academic literature: First, they show that individuals strongly and persistently react to (temporary) shocks in terms of career choice, which leads to a change in the allocation of talent between sectors. This adds to the broader debate about the allocation of talent, especially in the financial sector and in teaching.[2] Second, by observing that individuals at the top of the skill distribution switch between sectors, we infer that they possess general ex-ante talents and that even ex-post, after six years of specific PhD training, some individuals' skills are general enough to go back to the private sector. This relates to the born versus made debate in labor economics (e.g. Bertrand 2009, Oyer 2008). Third, we note that the predictions of a Roy-style model are strongly supported by the data in our quasi-experimental empirical setting. Fourth, our results imply that it is possible to lure talent to research by increasing wages.

For our empirical analysis we construct a new dataset of economists' career choices and publication output from publicly available sources. The dataset consists of graduation years and the degree granting universities of 13,624 PhDs since 1955 from the top 30 American institutions. We match each person with all their publications available on JStor and with an indicator for becoming a faculty member or a member of the American Economic Association (AEA) after the PhD. Thus, we can calculate the propensity to stay in academia and the publication output for each economist. Finally, we aggregate each cohort according to university and graduation year, and match the change in the unemployment rate at time of application to and at time of graduation from a PhD program. The change in the umemployment rate serves as a proxy for the macroeconomic (labor market) conditions and the state of the business cycle. We quantify the influence of the change in the unemployment rate at time of

[2]See, for example, Philippon and Reshef (2009), Bolton, Santos, and Scheinkman (2010) and Bacolod (2007).

application and at graduation on both the economists' propensity to decide in favor of academic employment and on their productivity.

Our paper is closely related to three distinct strands of the literature. First, as mentioned above, we contribute to the recent literature that analyzes the effect of business cycle shocks on individuals' careers. Kahn (2010) finds large and persistent negative wage effects of graduating from college in a worse economy. Oreopoulos, Wachter, and Heisz (2008) show that university graduates who enter the labor market during a recession experience a substantial initial loss of earnings, which fades only after 8–10 years, but that more highly skilled graduates suffer less because they switch to better firms rapidly.[3] Our study is the first to look at highly skilled individuals' response to these recession shocks by changing careers and its effect on the skill composition in one of the affected sectors. The results are consistent with those of Oreopoulos, Wachter, and Heisz (2008), as we find that more highly skilled individuals (are able to) respond more strongly.

The second strand of the literature to which we contribute is concerned with sorting in the labor market. While the papers above generally find that vertical, non-voluntary sorting (i.e., worse job placements whose effects are long-lasting) is the source of the negative impact of recession shocks, we consider horizontal, voluntary sorting (i.e., the individual's decision to continue their career in a different sector). In two papers in 2006 and 2008, Paul Oyer estimates the effect of vertical sorting on long term earnings and productivity by instrumenting MBAs' and economists' first placements with the state of the economy at the time of graduation. Combining Oyer's paper and ours on economics PhDs, it may well be that we underestimate the strength of our selection effect because of his placement effect and vice versa.[4]

There are plenty of well-known studies that are concerned with the sectoral selection of skills and the empirical content of the Roy model. Most of these papers employ "structural" econometric techniques while our quasi-experimental study doesn't need

[3]Other papers in this strand of the literature include Sullivan and von Wachter (2009),von Wachter, Song, and Manchester (2008), and Kondo (2008).

[4]For a more detailed explanation, see Section 4.4.

to rely on specific distributional assumptions about skills, for example.[5] We nonetheless find strong empirical support for the predictions of the Roy model. Another influential recent study by Philippon and Reshef (2009) describes the relationship between relative wages and human capital in the financial sector in the United States over the last century, but is unable to establish a causal effect of the former on the latter. In contrast, we are able to shed some light on the causal relationship between sectoral attractiveness and talent allocation.[6]

The third strand of the literature this paper deals with is concerned with the determinants of scientific productivity and their potential policy implications. Our study is most closely related to the papers that examine the impact of science funding on research productivity. Funding increases, like recessions, raise the attractiveness of the academic sector compared to the private sector. Goolsbee (1998) shows that up to 50% of a government spending increase goes into higher salaries for scientists and engineers. Suggesting that the supply of such knowledge workers is relatively inelastic, he argues that a large fraction of governmental research funding may in fact be ineffective and may only constitute a windfall gain for scientists. On the contrary, our results imply that the quantity and/or quality of researchers should strongly and persistently increase with more funding.[7]

The remainder of this paper proceeds as follows. We derive our theoretical predictions from a modified version of the Roy Model in the next section. Then we describe how we assembled our novel dataset of PhD economists' publication success. Section 4 presents and interprets the empirical results while Section 5 concludes.

[5]See Heckman and Honoré (1990) and, more recently, Keane and Wolpin (1997) and Lee and Wolpin (2006). An example of another non-structural paper on the Roy model is Borjas (1987).

[6]One paper that uses quasi-experimental identification to study sectoral selection is Bedard and Herman (2008). They examine the impact of economic contractions on the likelihood for enrollment in an advanced university degree program.

[7]Along these lines, Freeman and van Reenen (2009) assert that, at least in the long run, not only the number of scientists but also the selection of talent into science will increase due to higher salaries.

2 Theory

We are interested in how the selection of skills into academia and business varies with the state of the business cycle. This section modifies a standard Roy (1951) model for the problem at hand. The Roy model analyzes the self-selection of individuals with heterogeneous skills into sectors according to their highest expected earnings. In the following, we model two sectors—academia and business—into which individuals can self-select. Each individual has distinct skills (and therefore different wages) in each sector but can choose only one occupation. The main departure from the original Roy framework is that salaries in business vary with the business cycle and that the number of open positions in academia is assumed to be fixed.

2.1 Assumptions

Suppose that individuals are endowed with two skills, an academic skill α and a business skill β. There are two sectors, academia (A) and business (B), which produce outputs utilizing the respective skills. Individuals maximize their expected lifetime income by applying for jobs in academia or business.

The business sector is assumed to hire anyone with a wage w_t corresponding to their marginal product. The wage depends on the state of the business cycle y_t, i.e. a business employee's marginal product is higher in a boom (high y_t) and lower in a recession (low y_t):[8]

$$w^B(\beta) = \beta + y_t$$

On the other hand, salaries in the academic sector do not vary with the business

[8] We might adopt the more general notion of y_{app} and y_{grad} as the effect of the business cycle on current wage, but also on career outcomes in the future. This interpretation is consistent with recent papers that find substantial effects of the current business cycle on long term career outcomes, e.g. Oyer (2008) or Oreopoulos, Wachter, and Heisz (2008).

cycle and each worker is deterministically paid his marginal product[9][10]

$$w^A(\alpha) = \alpha.$$

To become an academic, an individual must decide for academia twice: first by applying to a PhD program (at time of application $t = app$) and a second time by pursuing an assistant professorship after the PhD (at graduation $t = grad$). At time of application, we assume that PhD programs admit the best N applicants according to academic skill and that there are always more applicants than available spaces. Thus, the entry into the doctoral program is competitive. This assumption seems reasonable as we consider the top 30 PhD programs in the US only. At graduation, we assume that the student can choose freely if he wants to stay in academia or enter the business sector instead. This assumption is more disputable: obtaining an assistant professorship at a (top)ranked institution is very competitive. However, conditioned on graduating from one of the top 30 US economics departments, it seems unlikely that a student cannot secure an academic job in a lower ranked institution, a teaching college, or a university outside the United States.

When taking his decision to apply for a PhD program, the applicant should also take account of the option value of having another choice about his career path after graduation. To simplify our problem, we assume that this option value is a constant, i.e. that it does not vary with the state of the macroeconomy at the time of application.[11] Thus, we can include it in the individual's expected earnings as an academic α.

[9] We can interpret α more generally as a combination of an individual's marginal product in academia and his non-pecuniary payoff for working in such an environment.

[10] All the results remain the same when we specify general wage functions $w^B = f(\beta, y)$ and $w^A = g(\beta, y)$ as long as $df/dy > dg/dy$. Proofs for this case are available from the authors upon request.

[11] In effect, this assumption amounts to imposing that the business cycle at time of application has no predictive power for the business cycle at graduation. We think that this is defendable as it takes on average six years to complete a PhD and we show in Appendix D that there is no correlation between the business cycle at time of application and graduation in our data. In general, we expect that our results should also hold in all of the cases where there is a reversal in the business cycle during that time frame, i.e., $Pr(y_{grad}^{Boom}|y_{app}^{Rec}) > Pr(y_{grad}^{Boom}|y_{app}^{Boom})$ and $Pr(y_{grad}^{Rec}|y_{app}^{Boom}) > Pr(y_{grad}^{Rec}|y_{app}^{Rec})$, and in a lot of cases where there is sufficiently strong mean reversion.

Given these assumptions, an individual compares the expected earnings from academia α and business $\beta + y_t$ at time of application and at graduation. He decides to apply for the academic sector (the PhD program or the assistant professorship) whenever

$$\alpha > \beta + y_t. \tag{1}$$

with $t \in \{app, grad\}$.[12]

2.2 Predictions

We are interested in how the selection of skills into academia and business varies with the state of the business cycle. To ease the exposition, we compare a generic boom cohort versus a generic recession cohort, i.e. $y^{Boom} > y^{Rec}$. All proofs are relegated to Appendix A.

Proposition 2.1 *For PhD applicants, the joint distribution of academic and business skills selected into the academic sector during a recession first order stochastically dominates (FSD) the corresponding boom distribution.*[13]

Figure 1 illustrates Proposition 2.1 when academic and business skills are distributed uniformly in the unit interval. Given our assumptions, an individual's career choice is governed by a "one-shot" decision, with those individuals for whom $\alpha > \beta + y_{app}$ preferring academia. During a boom (a high y_{app}^{Boom}), fewer individuals apply for academia than during a recession (a low y_{app}^{Rec}), which is depicted by a higher cutoff line for the former than for the latter. Academic employers always hire a fixed

[12] Furthermore we could have added to the model that a PhD constitutes an (uncertain) investment into academic (and business) skills. This is clearly an important feature of obtaining a graduate education and we did this in an earlier version of this section. However, as long as the skill update and the uncertainty about it can be assumed to be independent of the state of business cycle, it doesn't do anything to the predictions of the model other than adding noise.

[13] On the flipside, this implies that the joint distribution of skills selected into business during a boom first order stochastically dominates its recession counterpart. Note that in contrast to the well known result of the general Roy model (e.g. see Heckman and Honoré 1990), we can make a definitive statement about the stochastic dominance for a general distribution of skills here. This is due to the assumption of binding quantity constraints and the resulting competitiveness of the admission into the academic sector.

number, N, of graduates (PhDs & "only in boom" in boom, PhDs & "only in recession" in recessions) and therefore the distribution of skills for the recession cohort lies to the "North-East" of the corresponding distribution for the boom cohort.

[Insert figure 1 about here]

However, Proposition 2.2 shows that fewer of the PhDs who were admitted in a recession will decide to stay in academia and become assistant professors after the PhD.

Proposition 2.2 *For every realization of the state of the economy at graduation y_{grad}, a (weakly) higher fraction of the members of a "recession at time of application" cohort will not decide to stay in academia after the PhD.*

The proposition implies that, on average, cohorts of PhD graduates more often want to leave academia if they experienced a recession at the time of application. Figure 2 provides some intuition for the proposition. The academic skill cutoff, above which individuals will prefer academic employment after the PhD, "on average" moves down to the dashed line in the figure for a boom cohort and up for a recession cohort. Thus, in the figure, some individuals of the recession cohort want to exit academia and enter business after the PhD when the economy is out of recession, while everyone in the boom cohort wants to stay in academia. The recession graduates who want to leave academia here are the marginal ones who applied for the PhD "because of" the recession in the first place.

[Insert figure 2 about here]

Proposition 2.3 *For any given realization of the business cycle at graduation y_{grad}, the (partial) distribution of academic skills of the members of a "recession at application" cohort who want to stay in academia after the PhD first order stochastically dominates the distribution of skills of the corresponding members of the "boom at application" cohort.*[14]

[14] However, the stochastic dominance of the joint distribution of business and academic skills does not feed through in general.

Proposition 2.3 implies that, no matter how many more recession students than boom students leave academia after the PhD, the recession students who want to stay in academia are still better in each quantile of their (academic) skill distribution. In our specific example in Figure 2 we see that, although some mass of the recession cohort is cut off, the recession distribution of skills in academia still lies to the "North-East" of the boom distribution.

The effect of the business cycle at graduation (y_{grad}) is more straightforward. In a recession, more graduates decide to take up academic employment than in a boom. For these graduates who enter academia "because of" the business cycle the following equation holds: $\beta + y_{grad}^{Rec} < \alpha \leq \beta + y_{grad}^{Boom}$.

Proposition 2.4 restates this observation and Figure 3 provides a graphical representation in the special case of PhD graduates with academic and business skills distributed uniformly in the unit square.

Proposition 2.4 *A higher fraction of PhD economists decide to stay in the academic sector if they experience a recession at graduation.*

[Insert figure 3 about here]

Finally, we can reformulate the three propositions of the model into empirical predictions for our data:

1. Economists who experienced a recession at the time of application for the PhD are less likely to stay in academia after graduation (from Proposition 2.2).
2. However, if they stay, they are better researchers, both on average and in each quantile of their publication distribution (from Proposition 2.3).
3. Economists who experienced a recession at graduation from the PhD are more likely to stay in academia (from Proposition 2.4),
4. and, therefore, recession PhD graduates publish more on average (also from Proposition 2.4).

3 Data

We have collected a new dataset of career choices and individual productivity for a large sample of economists in the United States from 1955 to 2004. We aggregate the individuals into university year cohorts and match these with the change in unemployment in the year of application and the year of graduation.[15]

3.1 Economist Sample Selection

The bases of our dataset are the names, graduation years and PhD granting institutions of 13,624 economists who graduated from the top 30 US universities from 1955 to 1994. This data is obtained from the American Economic Association's (AEA) yearly "List of Doctoral Dissertations in Economics", which was published in the Papers and Proceedings issue of the "American Economic Review" until 1986 and in the "Journal of Economic Literature" thereafter. We supplement this information with the tier of the degree granting university according to the ranking of the National Research Council.[16]

3.2 Career Choice and Productivity Measures

We add an "academic" indicator which takes the value one if the economist was a faculty member in a US economics, business or finance department in 2001 or listed as a member of the American Economic Association, and otherwise zero. The US faculty directories are compiled by James R. Hasselback and made available on

[15] For the details of the data collection procedure, refer to Appendix B.

[16] The National Research Council rankings of economics graduate programs divide programs into tiers. The top three tiers include:

- Tier 1 (ranked 1–6): Chicago, Harvard, MIT, Princeton, Stanford, and Yale;
- Tier 2 (ranked 7–15): Columbia, Michigan, Minnesota, Northwestern, Pennsylvania, Rochester, California-Berkeley, California-Los Angeles, and Wisconsin-Madison;
- Tier 3 (ranked 16–30): Illinois-Urbana, Boston University, Brown, Cornell, Duke, Iowa, Maryland, Michigan State, New York University, North Carolina, Texas-Austin, Virginia, California-San Diego, University of Washington, and Washington University-St. Louis.

Source: "The American Economic Association Graduate Study in Economics Web Pages", accessed 2011-02-08, `http://www.vanderbilt.edu/AEA/gradstudents/`

his webpage.[17] AEA Membership data is obtained from the American Economic Association Directory of Members in 1970, 1974, 1981, 1985, 1989, 1993, 1997, 2003 or 2007. AEA membership serves as a proxy for faculty membership outside of the United States, because Hasselback's faculty directories strongly focus on US colleges and feature only very few foreign institutions.

In order to compare the oeuvres of different economists over time we calculate a consistent measure of publication productivity. For all economists in our sample, we collect the publication records in the first ten years after their graduation, multiply each publication of an author by its weight ("publication points") according to a dynamic journal ranking, and divide it by the number of coauthors of the paper. We then sum up all these contributions within the ten years after graduation to obtain a productivity measure for every individual in our sample.

More specifically, we match the PhD graduates with their publications (including journal title, number of pages and the number and identity of co-authors) in 74 journals listed in JSTOR, a leading online archive of academic journals. We select all journals contained in JSTOR for which a ranking was available. Thus we include all major publications in economics and finance except the journals published by Elsevier, most notably the "Journal of Monetary Economics" and the "Journal of Econometrics".[18] To ensure comparability among researchers, we restrict our attention to the first ten years after graduation. JSTOR currently only provides full publication data up to the year 2004. With the ten year requirement we can thus rightfully analyze the sample from 1955 to 1994 without placing younger researchers at a disadvantage.

Comparing the value of the collected publications records for different researchers over the decades is difficult because the relative impact of economics journals has changed substantially over time (Kim, Morse, and Zingales 2006). Therefore, we construct a dynamic journal ranking with decade specific publication points for each

[17]Source: "Faculty Directories", James R. Hasselback, accessed 2011-02-07, http://www.facultydirectories.com/

[18]Because we do not believe that either recession or boom cohorts systematically prefer or dislike Elsevier journals, this should be of no consequence.

journal from 1950 onwards. For the period from 1960 to the 1989, we use the ranking from Laband and Piette (1994), for the 1990s the equivalent ranking published in Kalaitzidakis, Mamuneas, and Stengos (2003), and for the 2000s the recursive discounted ranking available on the "ideas" webpage.[19] For the 1950s we were not able to find a journal ranking and thus decided to extrapolate a ranking for articles published in the 1950s from our 1960s ranking. A complete list of these journals with their associated publication points can be found in Table 6 of Appendix B.4.

In the Appendix C.1, we show that our results are robust to the use of other productivity measures.

3.3 Macro Data and PhD Entry Date

The main aim of our study is to relate the career decisions and the publication success of economists to a proxy for the state of the macroeconomy at the times of application to and graduation from their PhD program. As our data contains only person-specific graduation dates, we infer the application date by subtracting the median duration of a PhD of 6 years from the graduation date.[20] As proxy for the state of the business cycle, we use the change in the rate of unemployment from June of the preceding year to June of the considered year. Therefore, we measure the creation of new jobs right before the start of the PhD program (at application) and during the academic job market (at graduation).

The National Bureau of Economic Research (NBER) recession indicators are arguably the most convincing measures of recessions and all of the results in the paper hold (qualitatively) if we use them instead of unemployment change. However, binary indicators cannot carry information about the state of the economy as fine as continuous measures. Unemployment change is such a continuous measure and—out of several candidate variables that are available for the whole of our sample period—it

[19] Refer to "IDEAS/RePEc Recursive Discounted Impact Factors for Journals", last accessed 2009-07-31, `http://ideas.repec.org/top/top.journals.rdiscount.html`. Note, however, that the ranking on the website is updated continuously and thus is not exactly the same as we use in this study. The ranking that we use here was downloaded on 2009-07-31.

[20] The median duration of a PhD stayed almost constant at from five to six years since the 1970s (see Table 7 in Appendix B.5).

is the most strongly correlated with the NBER recession indicators.[21] Moreover, we believe that the change in unemployment is a good proxy for the change in university graduates' private sector employment opportunities, i.e. their outside option.

Refer to Section F.1 in the Appendix for our main results using the NBER recession indicators and GDP growth as measures of the business cycle as well as a table with the correlations of these measures, and with unemployment levels and GDP levels. Refer to Section F.3 for a sensitivity analysis with regard to the duration of the PhD.

3.4 Aggregation to University-Year Level

Finally, we group our graduates' publication performances and the indicator for being an academic or not into university-graduation year averages. Thus, we reduce the number of our observations from 13,624 individuals who graduated from institutions in tiers one, two, and three between 1955 to 1994, to 1068 cohort means. Because we do not use any explanatory or control variables that vary below the university-year level, this grouping entails no loss of information.

3.5 Descriptive Statistics

Table 1 provides summary statistics for the PhD cohorts' average productivity, the average probability to become an academic, and the macroeconomic variation.

The average ten-year productivity of a university-year cohort is about 31.49 publication points. In order to translate these publication points in terms of articles in a certain journal, one has to take into account that the importance of journals changes over time. For example, an article in the American Economic Review (AER) in the 1990s was worth 100 publication points while it was "only" worth 40.2 points in the 1980s.[22] Therefore, the average ten-year productivity of a university-year cohort in the full sample is about the equivalent of one-third of an AER article in the 1990s.

[21] Other potential proxies for the business cycle, for example job openings for university graduates or financial services activity, are not available for the entire study period. We want to thank Paul Oyer for sharing his data on financial services activity.

[22] Refer to Appendix B.4 for a more detailed interpretation.

The average probability to become an academic is about 60% and is slightly falling over time as we can see in Figure 4a. Conditioned on being an academic, the average ten-year cohort productivity totals 48.14 publication points. This is about 50% of an article in the AER in the 1990s.

Figure 4b depicts the average productivity of the PhD cohorts for every year in our analysis. More specifically, it distinguishes between the average productivity of all graduates and graduates that became an academic. As expected, we see that the performance measures move together to a substantial degree.

The change in the unemployment rate, our main independent variable, has a mean value of zero. The 10% quantile is -1.1 percentage points and the 90% quantile is 2.1 percentage points for the change in the rate of unemployment at time of application. At graduation, the 10% quantile is -0.9 percentage points and the 90% quantile 1.5 percentage points. Figure (4c) plots the change in the unemployment rate of each cohort at time of application and at graduation from 1955 to 1994. As expected the change in unemployment exhibits significant variation over the years.

[Insert Table 1 about here] [Insert Figure 4 about here]

4 Results

In the following we examine the empirical predictions derived from the modified Roy model.

4.1 Graphical Relationship and Empirical Specification

To get an initial sense of the degree to which the unemployment changes at time of application and at graduation are related to the career decisions and productivity of economists, the upper panel in Figures 5–7 plots these variables over time. Moreover, the lower panel in each figure illustrates with a kernel-weighted local mean smooth the degree of association of unemployment change and our outcome variables. The shaded areas indicate the 90% confidence interval. We employ an Epanechnikov kernel function and the rule-of-thumb bandwith estimator.

[Insert Figure 5, Figure 6 and Figure 7 about here]

In accordance with theoretical prediction 1, unemployment change at time of application seems to correlate slightly negatively with the propensity to become an academic (left panel of Figure 5). The publication productivity of academics in the left panel of Figure 6 correlates positively with unemployment change at time of application as in prediction 2. In accordance with predictions 3 and 4, a more positive change in unemployment at graduation seems to be associated with more PhDs staying in academia (right panel of Figure 5) and a better publication record (right panel of Figure 7), respectively.

In order to analyze more formally the relationships depicted in the Figures, we estimate the following model in three different specifications:

$$q_{i,t} = \beta \cdot y_{app,t} + \gamma \cdot y_{grad,t} + \delta \cdot \text{controls} + \epsilon_{i,t} \tag{2}$$

In the first specification, the outcome variable $q_{i,t}$ is the average publication output of a cohort of graduates from university i in year t. In the second specification, it is the average propensity to decide in favor of an academic career after the PhD, and in the third specification, $q_{i,t}$ is the average productivity of those who have decided to stay in academia after the PhD. The unit of observation in all three cases is the average of a given university in a given year, weighted by the amount of underlying individual observations. Moreover, the standard errors are clustered on the graduation year level, in order to allow for contemporaneous correlation between the outcome variables in the presence of regressors that do not vary within a given year.

The regressors $y_{app,t}$ and $y_{grad,t}$ of interest are the unemployment changes at time of application and at graduation, respectively. As control variables, we include dummies for the full set of interactions of university and graduation decade. These dummies pick up the (changing) quality differences of PhD education among universities over time and they control for the higher standards of publication in recent decades (e.g. Ellison 2002a, Ellison 2002b).[23]

[23] We have run regressions using recession indicators and GDP growth as a measure of the business cycle instead of unemployment change and we explored variants with linear and quadratic time

We estimate Equation (2) using linear regressions. To identify the average treatment effect of the change in unemployment on the respective outcome variable, we assume that the productivity and the career decisions of a cohort of (potential) PhD economists do not contemporaneously affect the business cycle in a given year. This assumption excludes potential reverse causality.[24] To be able to interpret β and γ exclusively as the causal parameters of the selection effect discussed in the theory section, we need an additional exclusion restriction to be satisfied: we assume that unemployment change affects a cohort's career decisions and publications only in terms of changing their choice of the sector to apply to (the selection effect). This assumption might not strictly be true in the light of the result of Oyer (2006) that the state of the business cycle affects an economist's first job placement and thus his productivity. We explain in Section 4.4 that given Oyer's result we might actually underestimate the causal effect of selection in our regressions due to leaving out the quality of the first job.

Table 2 summarizes the main regression results of the three specifications, each in one column. The following subsections explain the columns in turn.

[Insert Table 2 about here]

4.2 Effect on the Publications of all PhDs

The first column of Table 2 shows the effect of unemployment change on the publication output of an average PhD graduate in the sample. Unemployment change, both at time of application and at graduation, has a significantly positive effect on research productivity at the 5% and 1% level, respectively. These two results are also economically substantial: a cohort on the 90% quantile of unemployment change at time of application is expected to achieve 4.9 publication points more than a cohort on the 10% quantile. This is approximately 12% of the mean. Similarly, if we do the same calculation for the graduation cohort, the difference is 5.5 points, which is

trends. Our results are robust to these changes and reported in Appendix C.

[24] Furthermore, no third factor is allowed to influence both—the business cycle and, the career decisions and productivity—directly.

17.6% of the mean.[25]

The effect of unemployment change at graduation is in line with empirical prediction 4: PhDs who graduate during a recession publish more on average because more of them decide to stay in academia. Thus, the theoretical effect is at the “extensive margin” as opposed to an “intensive margin” effect in which those PhDs who would have stayed in academia anyway are publishing more if they graduate in recession than if they graduate in a boom.

The theory does not make a prediction which overall effect unemployment change at time of application should have on the publication output of an average PhD graduate. On the one hand, according to Proposition 2.1, graduates who experienced a recession at time of application constitute a better selection of individuals. On the other hand, according to Proposition 2.2, fewer of these individuals are expected to stay in academia and publish after the PhD. Empirically, it seems that the former effect dominates the latter, as a rise of unemployment at time of application is associated with a higher publication output of an average PhD.

4.3 Effect on Career Decisions

The second column of Table 2 reports how the unemployment change is related to economists' career decisions after the PhD.

PhD graduates are more likely to stay in academia when the economy is ailing, i.e. when there is a positive change in unemployment at graduation. The estimated coefficient is significant at the 5% level. This confirms empirical prediction 3 from the theory section and it is the source of the “extensive margin” effect on publication output per PhD student we mentioned above. Taking the estimates literally, a member of the cohort on the 90% quantile of unemployment change at graduation (+1.5%)

[25] Referring to Table 1 in Appendix B.4, the difference between the 10% and the 90% quantiles of unemployment change at time of application is 3.2. Multiplying this by the parameter estimate of 1.540 gives a difference in average productivity between “boom” and “recession” cohorts of 4.92 publication points. Referring to Table 6, this is about the number of publication points one gets assigned for an article in “Economica” during the 1990s. From Table 1, we also find that the “average” PhD graduate achieves 31.49 publication points. Similarly at graduation the difference between the 90% and 10% quantile is 2.4. Multiplying this with the estimate of 2.312, yields 5.549 publication points, which is about 17.6% of the mean of 31.49.

has a probability 3.24 percentage points higher to become an academic compared to a PhD student graduating on the 10% quantile (-0.9%). The average propensity to become an academic is 60%.

The theory also predicts that economists who experience a recession at entry to the PhD are less likely to stay in academia afterwards because some of them will enter only *because* of the recession (prediction 1). The evidence in Table 2 implies the existence of this effect, although the reported coefficient is not statistically significant.

More generally, we are not sure how to measure the decision between academia and business correctly. We think three different concepts of someone being an "academic" are conceivable: First, one could only consider faculty members of higher learning institutions as academics. This definition leaves out research staff at the IMF, the World Bank and at research institutes. Second, one could argue that the relevant distinguishing characteristic of an academic is producing novel and original research. And finally, one could more generally consider anyone an academic who works on research-related topics and upholds a relationship with the academic community.

The evidence reported in Table 2 is based on the third notion of an academic by classifying anyone as such who is either a faculty member or a member of the American Economic Association (AEA) after the PhD. Table 3 additionally shows the measures of being an academic according to the first two notions.

[Insert Table 3 about here]

Column two in this table shows the propensity to become an academic measured by whether graduates end up as members of faculty at an economics, business or finance department of a college or university in the United States according to the listings published by Hasselback (2001). We see that the direction of the effect is the same as in column one and in the main results table. However, the resulting coefficients are not statistically significant for either point in time. This might be the case because the employed faculty listings are not exhaustive. For example, faculty on leave are not included and we do not have faculty directories for other departments, such as law and agriculture. Our faculty listings are also strongly focused on US institutions. Thus, they miss many foreign graduates who become professors in their home countries and are members of the AEA.

Column three defines an academic as an individual who, according to our data, publishes at least one article in a ranked scientific journal after his or her PhD. The effect of the business cycle at the time of application is significant in the direction we expect from the theory while the effect at graduation is weak and not significant.[26]

Column 4 in Table 3 also shows regressions for the propensity to become an academic (according to our preferred academic measure) for a subsample of our graduates from the six top-ranked universities, i.e. the tier one schools. The effect here is strongly significant in the predicted direction for both unemployment change at graduation and at time of application. We interpret this as evidence that it is actually the individuals at the very top of the skill distribution which are most able to successfully switch back and forth between academia and business and who thus possess what one could call general skills. Overall, we conclude that the results at hand support the predictions made by our theory about the career decisions of PhD graduates.[27]

[26]This seems to confirm the different reasons for becoming an academic in relation to the two points in time: on the one hand, those individuals who become an academic because the economy is bad at graduation are just added at the extensive margin and some of them might not be able to write a ranked article. On the other hand, those individuals who experienced a recession at time of application and decide against academia after the PhD are of high academic ability according to the theory. Thus, a larger share of them would have been able to write a ranked article had they stayed in academia.

[27]One concern that was expressed to us is that foreign students may go back to their home country after the PhD. For example, Borjas (2006) shows that the share of foreign doctoral students has more than doubled since the 1970s. If hiring in the academic sector in the US is (somewhat) cyclical too, one might imagine that, in recessions, more foreign students go back to academic jobs in their respective home countries. We do not have information about whether students are natives or foreigners in our dataset. In terms of our model, if there are foreign academic programs whose hiring is less correlated with the US business cycle than US schools' hiring, this makes demand for economists more inelastic. If those graduates who take the option to go back more often in recessions appear in the faculty listings, the AEA listings, or if they publish in ranked journals, they are counted as academics. This fits our story. If they are not counted as academics, our estimates in Table 2 will understate the effect of the business cycle at graduation on the propensity to become an academic and, depending on whether it is the high-α or the low-α PhDs who react more to this, our estimates will under- or overstate the effect on the publications per graduate. Note that our model does not make predictions on the latter effect.

4.4 Effect on the Publications of Academics

The last column of Table 2 shows the results of regressing the publication output of individuals classified as academics on the change in the unemployment rate. The results here are robust to the sample selection according to any of the three definitions of an academic that were discussed above (see Table 23 in Appendix F.2).

The productivity of academics who experienced a recession at time of application is higher than that of academics who applied during a boom. This is in line with prediction 2 which states that the selection of PhD entrants is better during economically difficult times and that this better selection persists to the PhD graduates who stay in academia. The coefficient is significant at the 1% level and of economically relevant magnitude: comparing the average member of the cohort on the 90% quantile of unemployment change at time of application to a cohort member on the 10% quantile, the former is on average 10.47 publication points better than the latter. This is about 20% of the mean.[28]

In fact, prediction 2 states that a generic recession at time of application cohort should first order stochastically dominate a generic boom at time of application cohort with respect to academic skill. Therefore, not only the mean but the whole distribution of academic skills should shift to the right if unemployment increases. Table 4 shows the effect of the unemployment change on the distribution of publication output within each cohort using quantile regressions. A unit of observation is now an individual academic's publication output.[29] Among those PhDs who are considered academics according to our "academic" measure, 45 percent do not publish at all. We therefore restrict Table 4 to the effect of unemployment change on the median of the publication distribution and above. The estimates are in the predicted direction and significant for the upper quantiles of the publication distribution, but

[28]The 10% quantile of unemployment change at time of application is -1.1 percentage points, the 90% quantile is 2.10 percentage points and the difference is therefore 3.2 percentage points. Multiplying this difference with the mean estimate of 3.274 yields 10.4768. The mean productivity for an academic is 48.14 publication points.

[29]We only control for university tier–graduation decade fixed effects and their interactions here, because the quantile estimation becomes much less reliable with a large number of dummy controls. The standard errors are not clustered on the graduation year level as this is not straightforward to implement with quantile regressions.

they become insignificant for the lower quantiles. The reason for this is probably that the "academic" measure is not perfect at separating academics who do not publish from individuals who have left academia after the PhD. We know that there are more such individuals among the recession at application cohort, some of which are thus mistaken as low-skill academics. This downward-biases the difference between the publication distributions, most strongly so at the lower quantiles.[30]

The second line in column three of the main results, Table 2, reports the effect of unemployment change at graduation on the research productivity of academics. There are more PhDs deciding for an academic career if there is a recession at graduation. Without a specific assumption on the distribution of skills of PhD economists, our theory does not make a prediction whether the additional academics who enter at the "extensive margin" are of higher or lower academic skill than the average of those graduates who always decide to stay in academia after the PhD.

The empirical result in Table 2 suggests that on average PhD students with higher academic ability decide to stay in academia if the economy is in a state of recession compared to a state of boom. This is in line with the result already noted in Section 4.3, that it seems to be the individuals at the top of the skill distribution who are able to successfully move between the sectors. The estimated coefficient is significant at the 5% level. An academic graduating on the 90% quantile of unemployment change is on average 6.67 publication points better than an academic graduating on the 10% quantile. This is about 13% of the mean of 48.14.

At first glance, the result that academics who experience a recession at graduation are more successful at publishing than those who experience a boom, seems to contradict the findings by Paul Oyer (2006). He shows that PhDs who graduate during a favorable academic job market (which is correlated with economically good times in general) obtain better initial academic placements. He further shows that the first placement has a positive causal effect on an economist's research output by

[30]If we define an academic according to whether he publishes in a ranked journal instead of AEA membership or appearance in a faculty listing, and thus condition on non-zero publications, our quantile regressions yield positive and significant effects of unemployment change in line with the theory over the whole publication distribution.

instrumenting the first placement with the state of the academic job market during the graduation year.

However, we think that Oyer's and our result may not be contradictory, but that they could actually reinforce each other: suppose that both effects are relevant in reality—Oyer's placement effect and our selection effect. On the one hand, we would underestimate the effect of the business cycle at graduation on the skills selected into academia. This is because we would not take into account the worse placement a recession economist experiences on average, which would lower our measure of his skill, the publication output. Thus, the individuals selected into academia in recession would actually be better in terms of ex-ante skill than our estimate indicates. On the other hand, Oyer would underestimate the causal effect of the first placement on the research output of an economist. This is because he would not take into account the lower average ex-ante skill of a given economist during boom due to selection.

5 Conclusion

This paper investigated the effect of aggregate labor market conditions on the career choices and research productivity of economics PhDs in the United States. We documented that individuals who applied for—and graduated from—PhD programs during a recession produce substantially more research. Moreover, our results on the economists' career decisions provide strong evidence that the productivity effects arise from a self-selection into sectors driven by the state of the labor market. Using a Roy-style model of self-selection into sectors, we provided consolidated findings for the larger debate about the allocation of talent. For example, we think that it is reasonable to believe that the same effects that we found for economists should (qualitatively) matter for the allocation of talent into the financial sector or the teaching profession, too.

Given the severity of the crisis of 2008–09 and, in response, the large extent to which people flooded graduate schools with applications, our findings suggest that an exceptionally able selection of students may graduate from these cohorts. Further, we provide a rationale for countercyclical governmental funding of graduate education that goes beyond mitigating the adverse impact of recessions on individuals. If it is the aim to attract abler individuals to science and academia, it may be efficient to specifically target recession cohorts with extra funding and additional spaces in graduate programs.

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Appendices

A Formal Results and Proofs

Without loss of generality, we define the density function of academic and business skills on the unit square, i.e. $f(\alpha, \beta) \geq 0$ for $\alpha, \beta \in [0, 1]$ and zero otherwise. Furthermore let N be the number of places in the PhD programs as a fraction of the whole population of potential PhD students (i.e. N will be the fraction of all individuals that enter the PhD). As in the main text, we compare a generic boom to a generic recession cohort, i.e. $y^{Boom} > y^{Rec}$. Furthermore, a person applies for a PhD if he has skills such that $\alpha > \beta + y$.

In order to facilitate the proofs in the following, we do three more things: First, we define different sets of applicants to keep our notation concise in the rest of this section. Second, we define conditional probabilities to be able to compare different sets with each other. Third, we show that the least able (in terms of academic skills) individual admitted into academia in a recession is academically more able than the least able individual admitted in a boom. This result is used repeatedly in the proofs of the propositions.

1. The following distinct sets of applicants are used in the proofs and illustrated in Figure 8:

   - C(onstant) applicants, who enter academia no matter what happens in the business cycle.

   $$C = \{(\alpha, \beta) | \alpha \geq \alpha^{Rec} \alpha \wedge \alpha > \beta + y^{Boom}\}$$

   - B(usiness inclined), who only select themselves into academia if the business climate necessitates it.

   $$B = \{(\alpha, \beta) | \alpha \geq \alpha^{Rec} \wedge \beta + y^{Rec} < \alpha \leq \beta + y^{Boom}\}$$

- A(cademically inclined), who want to go to academia but only have the chance to if the group B members don't apply.

$$A = \{(\alpha, \beta)|\alpha^{Boom} \leq \alpha < \alpha^{Rec} \wedge \alpha > \beta + y^{Boom}\}$$

- E(xternals), who never go to academia.

Note that $A \cup C$ is the boom cohort and $B \cup C$ the recession cohort. Furthermore, from our assumption that there are always more people applying for a PhD-program than there are spaces, it follows that y has an upper bound.

2. We introduce the following notation for the probability of being member of the set X (or fulfilling the condition X) conditionally on being member of the set Y:

$$P_Y(X) = \frac{P(X \cap Y)}{P(Y)}.$$

This conditional probability is always within [0,1] and can be interpreted as the fraction of members of X who are member of Y. If the subscript Y is dropped, we refer to the the fraction of X compared to all potential applicants. As mentioned above, N is the the fraction of individuals actually entering the academic sector, i.e. in a recession $N = P(C \cup B)$ and in a boom $N = P(C \cup A)$.

3. We show that the cut-off value α^s is weakly higher in recession than in boom. A higher cut-off value implies that the least able (in terms of academic skills) individual admitted into academia in a recession is academically more able than the least able individual admitted in a boom.

Lemma A.1 $\alpha^{Boom} \leq \alpha^{Rec}$.

Proof of lemma A.1: Let $g_y(\alpha) := \int_0^{\alpha - y} f(\alpha, \beta)\, d\beta$ be the percentage of students with academic skill α who will apply to the PhD-program. Obviously $y^{Boom} > y^{Rec} \Rightarrow g_{y^{Boom}} \leq g_{y^{Rec}}$ as $f \geq 0$ for all (α, β). Therefore $\alpha^{Rec} \geq \alpha^{Boom}$ as the equality $\int_{\alpha^{Rec}}^1 g_{y^{Rec}}\, d\alpha = N = \int_{\alpha^{Boom}}^1 g_{y^{Boom}}\, d\alpha$ has to hold. ∎

Proof of proposition 2.1: : First, note that by the definition of A and B, $P_A(x \geq \alpha) = 0$ if $\alpha > \alpha^{Rec}$ and $P_B(x \geq \alpha) = 1$ if $\alpha \leq \alpha^{Rec}$. Second, as $P(A) = P(B) = N - P(C)$ it follows that $P_{A \cup C}(x \geq \alpha) \leq P_{B \cup C}(x \geq \alpha)$, which is the definition of first order stochastic dominance. As the argumentation holds analogously for the business skills, this implies a joint stochastic dominance of academic and business skills of the recession cohort compared to the boom cohort. $\blacksquare$

Proof of proposition 2.2: In case of $y_{grad} < y^{Boom}$ some or no people in set B leave the recession cohort and nothing changes in the boom cohort. If $y_{grad} \geq y^{Boom}$, all people in B leave. All remaining members of the recession cohort (who are member of set C and may or may not leave) are a subset of the boom cohort and therefore behave alike. Note that, as P(B) = P(A) and all members of B, but potentially only some members of A, leave for $y_{grad} \geq y^{Boom}$, there are always more leavers in the recession than in the boom cohort. $\blacksquare$

Proof of proposition 2.3: Let B' be a subset of B. We show that $C \cup B'$ first order stochastically dominates $C \cup A$ in the partial distribution of academic skill, which is the proposition for $y^{grad} < y^{Boom}$. It follows for all α that

$$P_{C \cup B'}(x \geq \alpha) = P_{C \cup B'}(C) P_C(x \geq \alpha) + P_{C \cup B'}(B') P_{B'}(x \geq \alpha),$$

and analogously $P_{C \cup A}(x \geq \alpha) = P_{C \cup A}(C) P_C(x \geq \alpha) + P_{C \cup A}(A) P_A(x \geq \alpha)$. This means that the percentage of members in C and B' who have an academic skill larger than some arbitrary α is the weighted sum of the percentage of members in C and of the percentage of members in B' who have at least such a high academic skill. The respective weights are the percentage of members of C in C union B' and the percentage of B' in C union B'. (Remember that $P_{C \cup B'}(C)$ is the percentage of members of C in the union of C and B'.)

Now one can show as in Proposition 2.2 :

- $P_{C \cup B'}(x \geq \alpha) \geq P_{C \cup B'}(C) P_C(x \geq \alpha) \geq P_{C \cup A}(C) P_C(x \geq \alpha) = P_{C \cup A}(x \geq \alpha)$ for $\alpha \geq \alpha^{Rec}$.

The first inequality holds by the decomposition of $P_{C \cup B'}(x \geq \alpha)$ above, the second inequality holds because $P(A) = P(B)$ and the equality holds because $P_A(x \geq \alpha) = 0$ for $\alpha \geq \alpha^{Rec}$ by definition of the set A.

- $P_{C \cup B'}(x \geq \alpha) = 1 \geq P_{C \cup A}(C) \underbrace{P_C(x \geq \alpha)}_{=1} + P_{C \cup A}(A) P_A(x \geq \alpha) = P_{C \cup A}(x \geq \alpha)$ for $\alpha < \alpha^{Rec}$. The first equality holds by the definition of C and B', the first inequality by the definition of probability measures (it cannot exceed one) and the second equality holds by the definition above.

These two statements taken together prove the first order stochastic dominance in the partial distribution of the academic skill for the recession cohort compared to the boom cohort.

Note, that the same argument can be made if $y^{grad} \geq y^{Boom}$ with A' and C' being subsets of A and C, respectively, and $B' = \emptyset$. This completes the proof. ∎

For the proof of the last proposition we require one further piece of notation: Let y^{Boom}_{grad} denote the business cycle variable if there is a boom at graduation and y^{Rec}_{grad} if there is a recession at graduation. Note that $y^{Boom}_{grad} > y^{Rec}_{grad}$ and therefore $w^B_{Boom} = \beta + y^{Boom}_{grad} > w^B_{Rec} = \beta + y^{Rec}_{grad}$.

Proof of proposition 2.4: The PhD students with $\{\alpha, \beta) | \beta + y^{Rec}_{grad} < \alpha \leq \beta + y^{Boom}_{grad}\}$ leave academia when there is a boom instead of a recession at graduation. As this set can be non-empty, weakly more students leave in a boom than in a recession. ∎

B Data Collection and Processing

This section explains in detail the data collection and processing procedure. Specifically, we explain how the sample of economists and their background variables were acquired and how we computed measures of publication success. An overview of the data sources is given in Table 5.

All employed programs are available from the authors upon request.

[Insert Table 5 about here]

B.1 Database for Economics PhD Graduates

To construct our sample of economists, we downloaded the PDF version of all issues of the American Economics Associations (AEA) yearly "List of Doctoral Dissertations in Economics" from JSTOR, an online journal repository from 1950 to 2006. The list was published in the Papers and Proceedings issue of the "American Economic Review" until 1986 and in the "Journal of Economic Literature" thereafter. The AEA "List of Doctoral Dissertations in Economics" specifies doctoral degrees conferred by U.S. and Canadian universities for every year since 1906. The name of the degree recipients and the year of graduation is provided to the American Economic Association by each degree granting university.

To convert the available PDF version of the AEA doctoral list into a text file, we used the optical character recognition (OCR) program included in the Adobe Acrobat 8 Professional Suite. The quality of the Adobe technology was best compared to several other programs we have tried. This read-in procedure worked well in general and it accelerated the compilation of the dataset but, as every automated procedure, it also entailed several problems and imperfections. In some cases the original PDFs were scans of old printed versions and, therefore, due to the quality of the source files, the character recognition of some records was erroneous.

Particularly, there were problems with the letter "r", which was mistaken as "n" or "i" from time to time. "O" was sometimes read as zero, "H" as "II", and "M" as "IVI". Also, dots sometimes were not readily recognized. We were able to correct faulty university names and graduation years because the set of those is finite. For example, we always replaced "IVIichigan" by "Michigan". Due to limited resources, we were not able to correct all errors in the name spellings. We decided to drop observations with names that contain characters or sequences of characters that are highly unlikely to be correct and thus had no chance to return accurate results in a query for publications in JSTOR.

In a next step we used regular expressions, a way to assign database fields for some string combinations, to convert the text file into a database format. The data structure of the AEA doctoral list is quite regular so this procedure worked reasonably well. On some instances, the employed regular expression was not able to determine the end of a data entry due to missing dots. However, this did not happen systematically.

As mentioned above, the read-in procedure delivered some faulty results. We believe that all these errors are orthogonal to our effect of interest and that they thus just add noise to our data. Nevertheless we want to test how many read in names are faulty: To do this, we first correct some years (perfectly) by hand and compare the resulting "complete" graduation numbers to graduation numbers published by the National Science Foundation (NSF). We find that the "complete" graduation numbers from the AEA list are about 90% of the NSF graduation numbers. Then, for every year, we compare the fraction of the "not corrected" number in our database to the number in the NSF data. This fraction fluctuates from 0.6 to 0.9, which suggests that in the worst case we lose about 40% of graduates due to the imperfect automated read-in procedure. In Figure 9 the number of NSF graduates and of graduates from our AEA list are plotted over time.

[Insert Figure 9 about here]

In the next step we supplemented the information with the respective tier of the degree granting university according to the National Research Council. The National Research Council rankings of economics graduate programs divide programs into tiers.

We dropped all graduates from universities not represented in this NRC ranking because we are not sure if the application process and research environment in these institutions are comparable to the universities in the first three tiers. In order to ensure robustness we also considered the Top 30 US universities according to the econphd.net ranking (as in Oyer 2006), which yielded the same results. The econphd.net ranking is available online on `http://econphd.econwiki.com/rankings.htm` (last accessed 2011-02-07).

B.2 Indicator for Being an Academic

To complete the person-specific background variables, we add an indicator if a PhD graduate became an "academic" later on. We define "academics" according to the three concepts explained in section 4.3 - those who are faculty members, those who are faculty members or AEA members, and those who publish at least one ranked article. While the last concept derives from our publication measure explained in the next subsection, the data collection for the first two measures is described here.

Data about faculty membership in US economics, business or finance departments is acquired from the webpage of James R. Hasselback from the University of West Florida who regularly compiles U.S. faculty directories.[31] Unfortunately, there is no comprehensive database about faculty members of non-US universities, researchers in other US university departments, like law and agriculture, and academics in institutions other than universities, e.g. World Bank researchers. To construct a proxy for belonging to these groups, we analyze the membership records of American Economic Association. We think that the likelihood of being an AEA member is higher, if the graduate decided to become a member of the academic community.[32]

The faculty listings and the AEA membership directories are only available as PDF. Therefore, we again use the Adobe OCR program and regular expressions to translate them into a database file. We use Apache Lucene, an information retrieval library, to match the data on graduates with the faculty listing and the AEA membership. This is necessary because some students drop their second name over the years or abbreviate it. As is common for search engines, Lucene employs a scoring algorithm based on the similarity of the name of the graduate and the name in the documents.[33] For the faculty directory (and a sample of the AEA members), we checked the matches found by hand to ensure accuracy.

[31] "Faculty Directories," James R. Hasselback, accessed 2011-02-07, `http://www.facultydirectories.com/`

[32] Specifically, we take the AEA directory of members in 1970, 1974, 1981, 1985, 1989, 1993, 1997, 2003 and 2007.

[33] For a discussion of the scoring algorithm of Lucene please refer to "org.apache.lucene.search - Class similarity," last accessed 2011-02-07, `http://lucene.apache.org/java/2_4_0/api/org/apache/lucene/search/Similarity.html`.

B.3 Publications

After compiling the database of graduates, we used a program to match each entry with its publication record in JSTOR. To do this, we use the newly available XML application programming interface of JSTOR, called "Data for Research" (DfR).[34] Specifically, we entered the names and given names of all researchers contained in our database and extracted all recorded publications with journal title, number of pages and the number and identity of coauthors in the first 10 years after their graduation. To be as specific as possible, we restricted our search to articles classified as "research articles" published in English language in the fields of economics, business and finance.

The restriction to articles published ten years after graduation (as in Oyer 2006), has three reasons: First, it improves the specificity of the data processing, because economists with the same name who were born in different decades are not merged but kept as different persons. Second, the quality of an economist is arguably best revealed in the first decade after PhD graduation. Academic researchers are highly motivated (incentivized) in this period because their tenure decision depends on the publication record of these first years. Finally, graduates from more recent years would be disadvantaged if we did not restrict the time frame. Currently JSTOR provides full publication data up to the year 2004, so the last individuals we can rightfully analyze following our ten year requirement are those who graduated in 1994.

B.4 Ranking Methods and Interpretation of the Productivity Measure

To measure the productivity of each individual on an cardinal scale, we have to value each publication in the record. This poses three challenges: First, the relative weight of an article in a certain journal compared to an article in another journal is a

[34] JSTOR (`http://www.jstor.org/`) (last accessed 2011-02-07) is a leading repository for archiving academic journals which contains (in July 2010) around 3.1 Million research articles for all sciences with the first article published in 1545. For the DfR interface please refer to "JSTOR Data for Research," last accessed 2011-02-07,`http://dfr.jstor.org/`.

constant matter of discussion in the profession. Second, comparing the value of publications over the decades is difficult because the relative impact of economics journals has changed substantially over time (Kim, Morse, and Zingales 2006). Third, by summing up the contributions of different publications over ten years, the resulting number becomes hard to interpret. We adress these challenges by showing the robustness of our result for several ranking methodologies with different strengths and weaknesses below.

Our preferred method is a citation ranking based on the methodology of Laband and Piette (1994). The authors of this study use the citations to articles in a particular journal (excluding self-citations) as a measure of its quality or impact. Their paper presents the journal impact factors from the 1960s to the 1980s, while Kalaitzidakis, Mamuneas, and Stengos (2003) use the same method for the 1990s and the recursive discounted ranking on the ideas.org ranking page delivers us the impact factors for the 2000s.[35] For the 1950s we were not able to find a journal ranking and thus decided to extrapolate our 1960s ranking back to articles published in the 1950s. In total, we collect impact factors of 74 ranked journals in economics, business and finance for five decades. Table 6 provides an overview of the dynamic ranking of the top forty journals used in this study.

The outcome measure in Table 6 is denominated in publication points. The best journal in each decade receives 100 points and all others are scaled accordingly. For example, in the 1960s, a single-authored Econometrica article is worth 46.6 points while it is worth 96.8 points in the 1990s. The impact of the American Economic Review (AER) changed even more dramatically: It has been the leading journal in the 1960s and 1990s with 93.3 and 100 respectively. In contrast, in the 1970s, 1980s and 2000s it was "only" a top tier journal with 30-40 publication points. Consequently, when trying to interpret our results above in terms of actual papers, we need to mention the journal and the decade (e.g. "one third of an AER article in the 1990s").

[35] "IDEAS/RePEc Recursive Discounted Impact Factors for Journals," last accessed 2011-02-07, `http://ideas.repec.org/top/top.journals.rdiscount.html`. Note, that this ranking is updated continuously and thus its online version at the time of reading is not exactly the same as the one we use.

[Insert Table 6 about here]

Reassuringly, we show in section C.1 that our results are extremely robust to using several other intuitive productivity measures: publication points assigned according to the currently very popular h-index, raw counts of articles written, and, most notably, counts of articles in the five top economics journals (as in Oyer 2006) plus the Journal of Finance.

B.5 Imputing the PhD Entry Date

As mentioned in section 3.3, we have to impute the approximate application date to the PhD.

[Insert Table 7 about here]

According to Table 7, the median duration of a PhD stayed almost constant around five to six years since the 1970s. We therefore subtract six years from the graduation date and then use the change in the unemployment rate during the preceding year as an indicator for the state of the macroeconomy at application.

For example, if a hypothetical graduate student obtained his doctorate in 2009, he is likely to have started the program either in August 2003 or August 2004 and must have applied either in the fall of 2002 or 2003. Consequently, we proxy the change in the outside option at application for a student who graduates in 2009 with the change in the unemployment rate from summer 2002 to summer 2003.[36]

C Robustness Checks

In this section we show that our results are robust when we use several different measurement concepts for publication productivity. We also consider the subsample of the graduates from the elite tier one institutions.

We restate our main findings in Table 8: A recession at application leads to a more productive selection of academics (column 3). The propensity to become an

[36]Of course, we cannot be sure that the median number of years is a good measure for the duration of the PhD for the considered graduate. There is micro data on the duration available with the National Science Foundation Survey of earned doctorates but access is limited to on site use.

academic is decreasing with unemployment change at application and increasing with unemployment change at graduation (column 2). Cohorts graduating in a recession are publishing more (column 1).

[Insert Table 8 about here]

C.1 Alternative Measures for Productivity

One might be concerned that our dynamic productivity measure does not properly capture the actual achievements of an academic. We consider three alternative measures of academic productivity in Tables 9 and 10: the number of top journal articles, the h-value and the raw number of articles. We classify articles in the "Econometrica", "The American Economic Review", "The Quarterly Journal of Economics", "The Review of Economic Studies", "The Journal of Political Economy" and "The Journal of Finance" as top journal articles. The h-index (Hirsch index or Hirsch number) is a currently very popular measure based on citations and number of articles. An economist has index h if h of his N papers have at least h citations each, and the other N - h papers have at most h citations each. The last measure is the raw number of articles written as recorded in JSTOR.

[Insert Table 9 and Table 10 about here]

All results in Tables 9 and 10 point in the same direction as the dynamic performance measure in the main text and as the selection theory predicts. Out of the effects predicted by the theory, only the effect of the unemployment change at application on the number of articles of academics is not significant. Thus, our results are robust to the use of different productivity measures.

C.2 The Tier 1 Subsample

We also consider the subsample of economists who graduated from the elite tier 1 schools and repeat all our regressions for these highly skilled individuals. According to Table 11, the magnitude of the effects appears to be larger in all considered dimensions. With regard to productivity, the estimates are significant on conventional levels. The only exception is the effect of unemployment change on productivity at graduation, which is insignificant but correctly directed. The effect at application and at graduation on the propensity to become an academic for our preferred measure is strong and highly significant. If we consider the two alternative measures of being an academic, the result is weaker, not significant, but in the correct direction (see Table 12).

[Insert Table 11 and Table 12 about here]

Tables

Table 1: Summary Statistics

	mean	sd	min	max	p10	p90
Productivity	31.49	84.89	0.00	1738.10	0.00	93.80
Productivity Academic	48.14	103.84	0.00	1738.10	0.00	144.72
Academic	0.60	0.49	0.00	1.00	0.00	1.00
Unempl Change (Application)	-0.01	1.13	-2.10	2.90	-1.10	2.10
Unempl Change (Graduation)	0.02	1.03	-2.10	2.90	-0.90	1.50
Observations	13624					

Table 2: The main regression results

	Productivity	Academic	Productivity
Unempl Change (Application)	1.540**	-0.891	3.274***
	(0.661)	(0.576)	(0.945)
Unempl Change (Graduation)	2.312***	1.354**	2.738**
	(0.645)	(0.607)	(1.199)
Subsample	All	All	Academic
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Different measures for being classified as academic

	Academic	Faculty	Publish	Academic
Unempl Change (Application)	-0.891	-0.427	-0.979**	-1.716***
	(0.576)	(0.475)	(0.457)	(0.579)
Unempl Change (Graduation)	1.354**	0.535	0.414	2.866***
	(0.607)	(0.409)	(0.397)	(0.938)
Subsample	All	All	All	Tier 1
Univ-Decade Dummies	Yes	Yes	Yes	Yes
Observations	1068	1068	1068	234

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Quantile regression for the academic subsamples

	50%	65%	80%	95%
Unempl Change (Application)	-0.000***	0.445	3.699***	9.343*
	(0.000)	(0.674)	(1.300)	(5.022)
Unempl Change (Graduation)	-0.000***	1.130	3.869***	0.623
	(0.000)	(0.708)	(1.344)	(5.221)
Subsample	Academic	Academic	Academic	Academic
Tier-Decade Dummies	Yes	Yes	Yes	Yes
Observations	8222	8222	8222	8222

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Data sources

Variable	Description	Source
Personal information of graduates	Name, University and Graduation year	AEA "List of Doctoral Dissertations in Economics" of 1955 to 2004
Faculty membership	Faculty directory of (mainly American) Economics, Business and Finance departments by John R. Hasselback	"Faculty Directories," James R. Hasselback, accessed 2011-02-07, `http://www.facultydirectories.com/`
Membership in the AEA	Membership data of the American Economic Association in 1970, 1974, 1981, 1985, 1989, 1993, 1997, 2003 and 2007	Supplement to the Papers and Proceedings Issue in the respective year digitalized by JSTOR
University ranking	Tier of a university according to the National Research Council	"The American Economic Association Graduate Study in Economics Web Pages," accessed 2011-02-08, `http://www.vanderbilt.edu/AEA/gradstudents/`
Publication records	Publications in 74 journals listed in the JSTOR online repository, from 1955 to 2004	"JSTOR Data for Research," last accessed 2011-02-07, `http://dfr.jstor.org/`.
Journal rankings	Citation ranking of journals in Economics, Business and Finance from 1950 to 2000	Laband and Piette (1994), Kalaitzidakis, Mamuneas, and Stengos (2003), Kim, Morse, and Zingales (2006) and "IDEAS/RePEc Recursive Discounted Impact Factors for Journals," last accessed 2011-02-07, `ideas.repec.org/`
Measure of the business cycle	seasonally adjusted change in unemployment or GDP growth from 1949 to 1994	Thomson Reuters Datastream
Duration of the PhD	Median years between registration and graduation from the PhD for 1977, 1986, 1996, 1997, 2001	National Science Foundation, Stock and Siegfried (2006), Hansen (1991)
Number of Graduates (NSF list)	Number of admitted and graduating PhDs according to the "NSF Survey of Earned Doctorates/Doctorate Records File" of the National Science Foundation	"WebCASPAR Integrated Science and Engineering Resource Data System - NSF Survey of Earned Doctorates/Doctorate Records File," National Science Foundation, last accessed 2011-02-08, `https://webcaspar.nsf.gov/`
econphd.net ranking	University ranking according to econphd.net	"Rankings." last accessed 2011-02-07, `http://econphd.econwiki.com/rankings.htm`

Table 6: Ranking of journals in different decades.

Rank	Journal (ordered by 2000 rank)	1960	1970	1980	1990	2000
1	The Quarterly Journal of Economics	65.6	16.2	41.6	58.1	100
2	Econometrica	46.6	31.6	78.4	96.8	68.7
3	Journal of Economic Literature	-	100	100	18.8	63.5
4	The Review of Economic Studies	100	30.7	40.7	45.2	54.3
5	Brookings Papers on Economic Activity	-	96.9	15.9	0.7	51.5
6	The Journal of Political Economy	63.5	59.1	63	65.2	49.8
7	Economic Policy	-	-	-	-	45.7
8	Journal of Labor Economics	-	-	15.4	12.8	45.5
9	The American Economic Review	93.3	34.5	40.2	100	39.9
10	The Journal of Economic Perspectives	-	-	23.3	34.3	39.8
11	The Review of Financial Studies	-	-	-	-	39.2
12	Journal of the European Economic Association	-	-	-	-	38.6
13	The RAND Journal of Economics (Bell Journal of Economics)	-	39.5	40.2	11.4	38.2
14	The Journal of Finance	37.8	14.6	34.1	34.1	31.1
15	The Review of Economics and Statistics	59.8	12.4	6.5	28	21.7
16	Journal of Business & Economic Statistics	-	-	7.9	38.4	20.8
17	The Economic Journal	47.5	28	23.9	20.7	20.5
18	Journal of Applied Econometrics	-	-	-	16.6	19.1
19	Journal of Money, Credit and Banking		18.5	22.1	18.6	18.6
20	The World Bank Economic Review	-	-	-	5.7	18.5
21	International Economic Review	35.1	19	12.3	23	18.4
22	IMF Staff Papers	-	-	-	5.1	18.3
23	Journal of Law, Economics, & Organization	-	-	-	4.1	16.1
24	Journal of Law and Economics	51.8	43.3	33.1	3.9	14.1
25	The Journal of Human Resources	-	13.6	4.6	21.3	13.4
26	Journal of Population Economics	-	-	-	2.41	10.6
27	The Scandinavian Journal of Economics	2.5	7.1	2.1	10.7	9.2
28	The Journal of Business		18.5	37.4	8.7	8.7
29	The Journal of Industrial Economics	14.9	16.4	16	3.85	8.7
30	The World Bank Research Observer	-	-	-	0.9	8.5
31	The Journal of Financial and Quant. Analysis	-	10.8	20	2.1	7.9
32	Oxford Economic Papers	35.2	16.8	25	3.7	7.9
33	Economica	20.7	36.2	4.1	4.5	7.2
34	Economic Theory	-	-	-	22.4	6.8
35	Industrial and Labor Relations Review	17	18.8	23.4	-	6.1
36	Econometric Theory	-	-	3.3	45.8	5.9
37	The Canadian Journal of Economics	-	11.8	10.2	5.09	5.6
38	The Journal of Legal Studies	-	-	51.6	5.4	5.4
39	Financial Management	-	-	-	-	5.1
40	Journal of Accounting Research	-	-	-	-	4.2

Note: These are the first 40 out of 74 journals. The rankings for the 1960s, 1970s and 1980s are taken from Laband and Piette (1994) and the ranking for the 1990s is from Kalaitzidakis, Mamuneas, and Stengos (2003). For the 2000s, we normalize the current discounted recursive impact factors ranking from the IDEAS RePEc website (`http://ideas.repec.org/top/top.journals.rdiscount.html`, last accessed 2011-02-07) to make it comparable to the other rankings.

Table 7: Duration of a PhD

Year	1977	1986	1996	1997	2001
	5.7	6.3	5.3	5.25	5.5
	Median years of registered time to PhD	Median years of registered time to PhD	Time to degree	median time-to-degree	Time to degree
Source	Hansen (1991)	Hansen (1991)	NSF*	Stock and Siegfried (2006)	NSF*

*NSF duration data includes masters degrees, therefore we subtract 1.5 years

Table 8: Main regression results

	Productivity	Academic	Productivity
Unempl Change (Application)	1.540**	-0.891	3.274***
	(0.661)	(0.576)	(0.945)
Unempl Change (Graduation)	2.312***	1.354**	2.738**
	(0.645)	(0.607)	(1.199)
Subsample	All	All	Academic
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Alternative productivity measures - Full sample

	Top Journals	h-index	# of Articles
Unempl Change (Application)	0.016	1.172	0.012
	(0.010)	(1.110)	(0.032)
Unempl Change (Graduation)	0.040***	3.980***	0.050**
	(0.009)	(0.869)	(0.022)
Subsample	All	All	All
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1068

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Alternative productivity measures - Academics

	Top Journals	h-index	# of Articles
Unempl Change (Application)	0.035**	3.161**	0.057
	(0.014)	(1.558)	(0.047)
Unempl Change (Graduation)	0.050***	4.838***	0.047
	(0.014)	(1.552)	(0.044)
Subsample	Academic	Academic	Academic
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1047	1047	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Main regression results (Tier 1)

	Productivity	Academic	Productivity
Unempl Change (Application)	5.394**	-1.716***	9.864***
	(2.123)	(0.579)	(2.935)
Unempl Change (Graduation)	4.347*	2.866***	3.969
	(2.385)	(0.938)	(3.449)
Subsample	Tier 1	Tier 1	Academic Tier 1
Univ-Decade Dummies	Yes	Yes	Yes
Observations	234	234	232

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Alternative measures for being academic (Tier 1)

	Academic	Faculty	Publish
Unempl Change (Application)	-1.716***	-0.080	-1.276
	(0.579)	(0.822)	(0.881)
Unempl Change (Graduation)	2.866***	0.719	0.532
	(0.938)	(0.474)	(0.786)
Subsample	Tier 1	Tier 1	Tier 1
Univ-Decade Dummies	Yes	Yes	Yes
Observations	234	234	234

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures

Figure 1: Selection with a U(0,1) distribution of both skills at application.

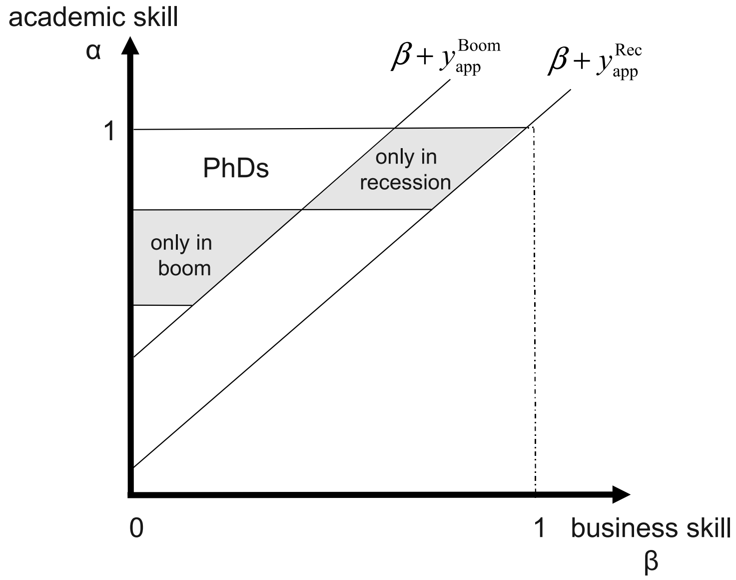


Figure 2: Selection with a U(0,1) distribution of both skills at graduation.

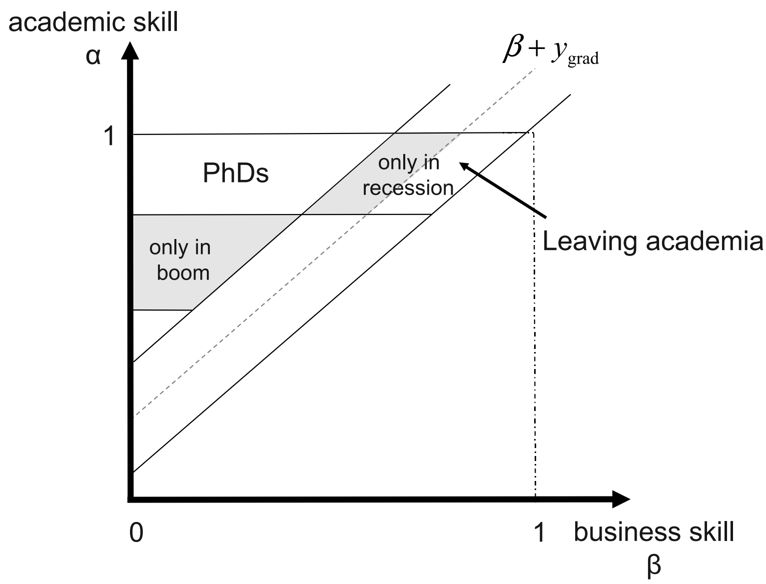


Figure 3: Selection at graduation.

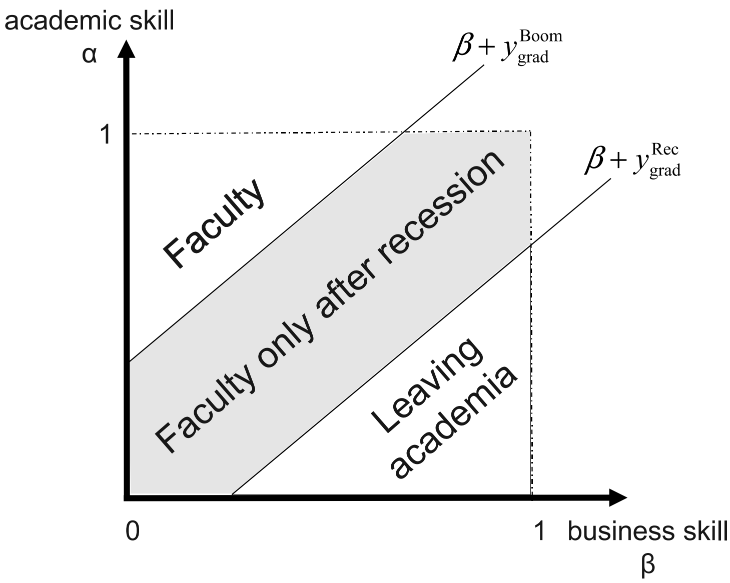
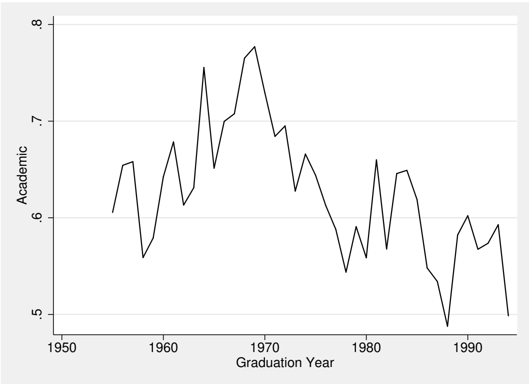
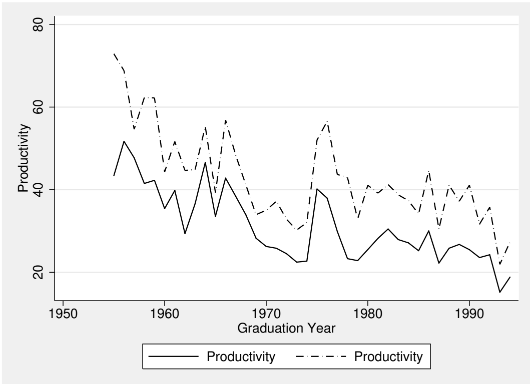


Figure 4: Dependent and independent variables over time

(a) Probability to become an academic



(b) Research productivity



(c) Unemployment Change

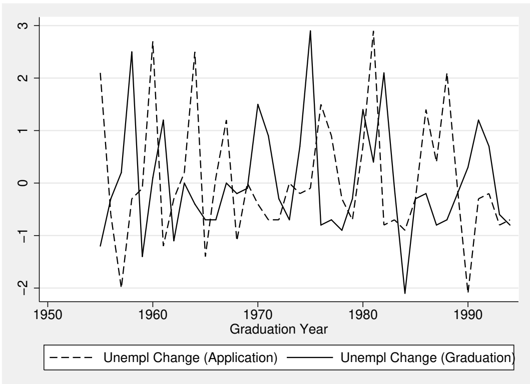
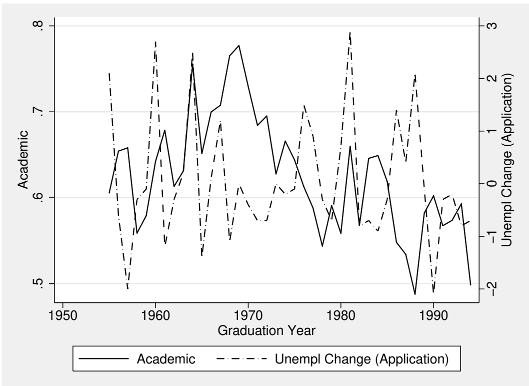
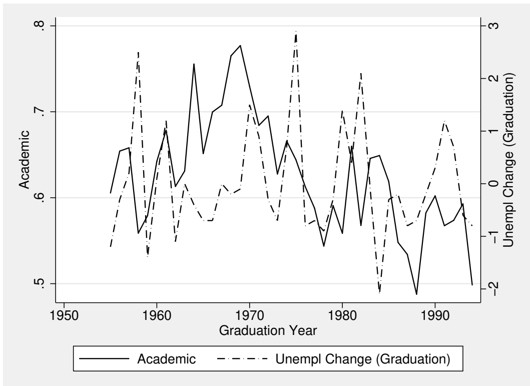


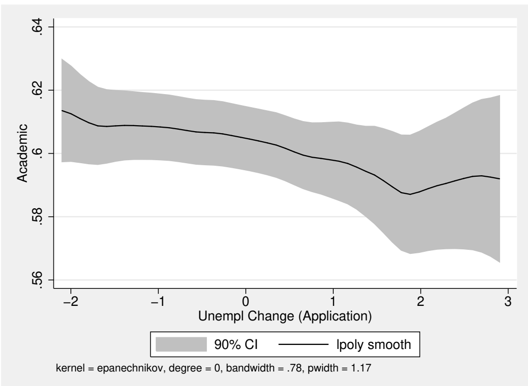
Figure 5: Fraction of academics and unemployment change



(a) at application



(b) at graduation



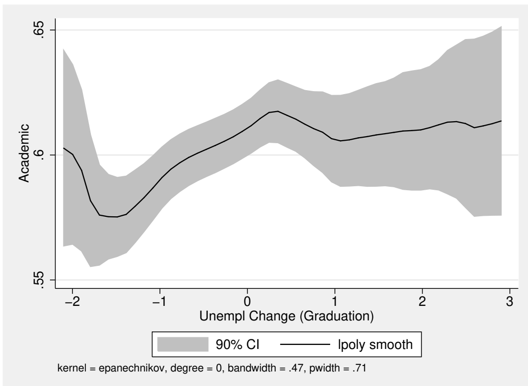
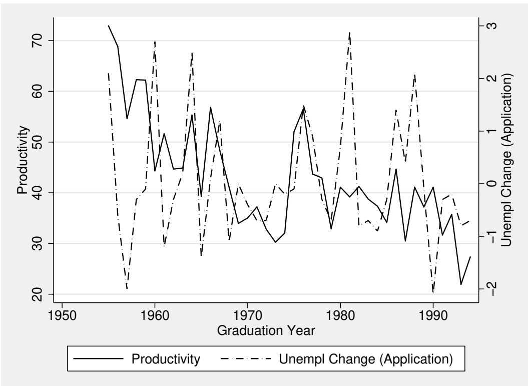
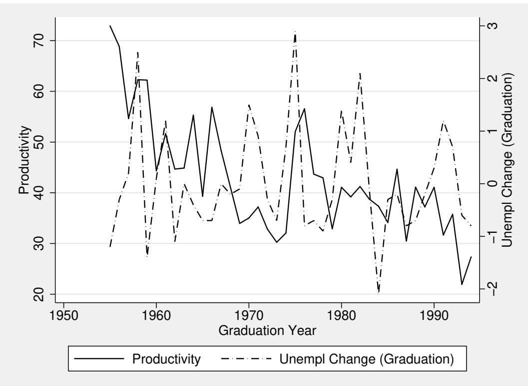


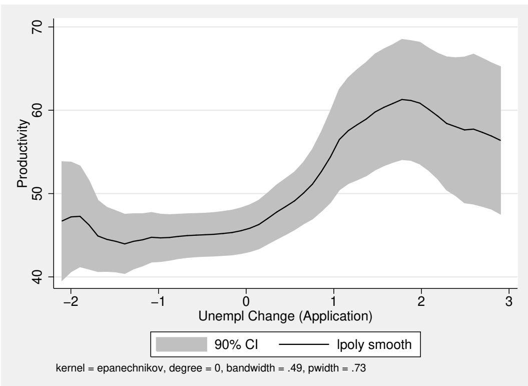
Figure 6: Productivity of academics and unemployment change



(a) at application



(b) at graduation



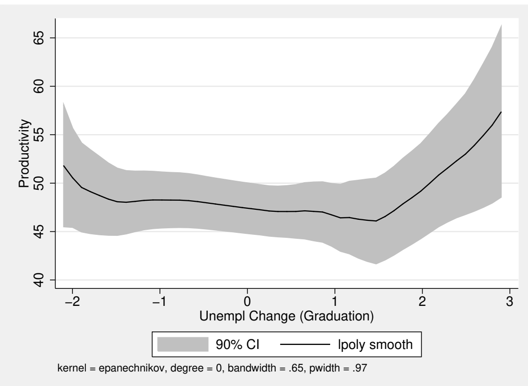
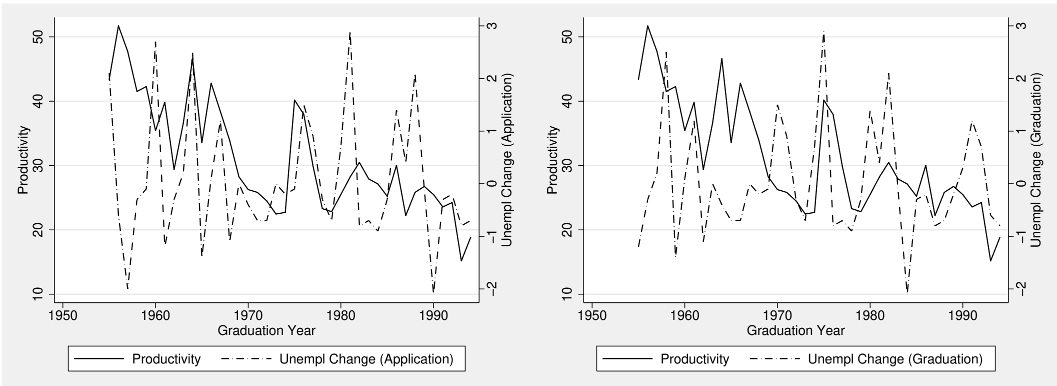


Figure 7: Productivity and unemployment change



(a) at application

(b) at graduation

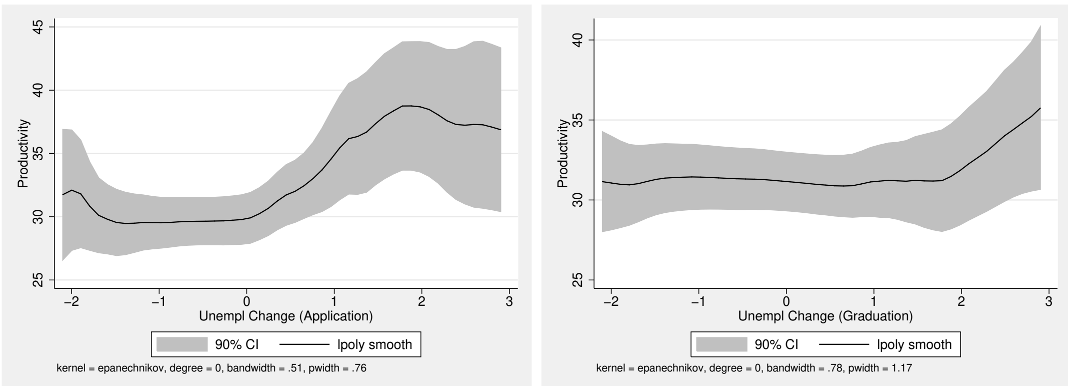


Figure 8: Example with a U(0,1) distribution of both skills.

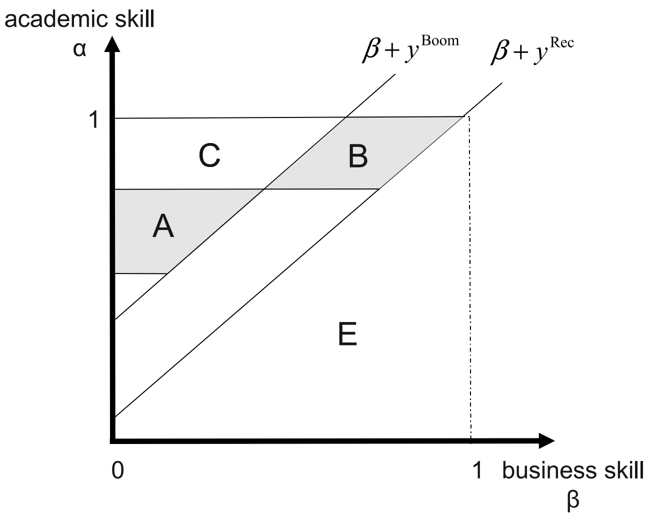
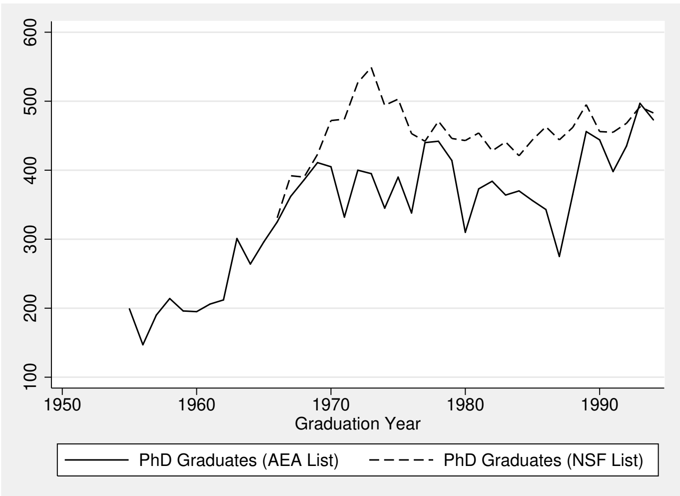


Figure 9: Number of graduates according to the NSF and the AEA list over time



Appendices: not intended for publication

D The Relationship Between (Potentially) Confounding Factors and the Business Cycle

This section addresses potential concerns about factors that might confound our results and analyzes possible impacts on our estimates. In the following we address concerns about the size of the entry and exit cohort, the attrition rate and the timing of graduation. Lastly, we adress a potential correlation of the business cycle at application and graduation.

In order to do this, we calculate the number of graduates from our dataset (in the following listed as "# of graduates (AEA)") and match it with the unemployment change at application and at graduation. Then, we supplement this data with data from the National Science Foundation's "Survey of Earned Doctorates".[37] From there we obtain the the number of PhD entrants and graduates for our top 30 universities since 1977. Using this data, we are able to estimate the attrition (dropout) rate of each cohort as the difference of the number of entrants minus graduates divided by the number of entrants. We report the partial correlation coefficient of unemployment change at application and at graduation with application and graduation numbers in Table 14. In order to obtain the correct standard errors we aggregate the data to yearly averages.

[Insert Table 14 about here]

The first concern one might have is that the number of students admitted to the PhD systematically increases (decreases) in recessions. Within the framework of our model, this would weaken (strengthen) the selection effect at application. The estimated coefficient of unemployment change at application might then be underestimated (overestimated). According to Table 14, we cannot reject that the relation

[37] This survey is publicly available through the WebCASPAR Interface: "WebCASPAR Integrated Science and Engineering Resource Data System - NSF Survey of Earned Doctorates/Doctorate Records File," National Science Foundation, last accessed 2011-02-08, `https://webcaspar.nsf.gov/`.

of the number of entrants to the PhD and the change in unemployment differs from zero on conventional significance levels (p-value of 67.5%). In Figure 10 the number of graduates in our data and the unemployment change at application are depicted.

[Insert Figure 10 about here]

Second, one might be concerned that the attrition (or dropout) rate during the program may systematically differ between recession and boom cohorts. On the one hand, some business-inclined individuals who entered the PhD in order to bridge a recession might return to the private sector before they actually obtain the PhD. If this were the case, we would underestimate the effect of unemployment change at application on economists' career decision after the PhD (the "academic" variable). The reason is that many of those who would want to switch would have already done so before we consider them in our population of graduates. On the other hand, there might be a higher dropout rate for the boom cohort because its individuals are of lower academic quality. In this case, our parameters would underestimate the effect of unemployment change at application on the performance of graduates and academics. According to the correlation Table 14, our estimate of the attrition rate is not significantly correlated with unemployment change at application or graduation.

Third, PhDs might time their graduation in order to circumvent entering the private or the academic job market during a time of recession.[38] The effect of such a graduation timing on our parameter estimates would depend on whether the high- or the low skilled bring their graduation date forward (or delay it). For example, if in a recession students with low academic talent delay their end of the PhD, we overestimate the effect on productivity at graduation, but underestimate the effect on becoming an academic. This would attenuate our effect of the business cycle on productivity at application. Table 14 reports the correlation of graduation numbers and unemployment change according to the NSF data and the AEA doctoral listings, respectively. Reassuringly, graduation numbers seem not to be at all related to the state of the business cycle.

Finally, a last concern might be that, contrary to our assumption in the model,

[38] Oyer (2006) documents that also academic job offers decline during recession.

the business cycle is systematically correlated with itself in the six years between a cohort's application and graduation. Table 13 reports this and the contemporaneous correlation between the unemployment change and GDP growth. Unsurprisingly both measures are strongly contemporaneously related. However, there is no significant correlation, neither of unemployment change nor GDP change, between the time of application and graduation. If at all, there may be a very slightly reversing relationship over the six years. This could imply that we potentially underestimate the effect of the business cycle on academic performance because a recession cohort at graduation is more likely a boom cohort at application (and thus is inherently not as able) and vice versa for a boom cohort at graduation. For the same reason we might in this case overestimate the effect of the business cycle on the career decision (i.e. the academic variable) at application and at graduation.

[Insert Table 13 about here]

E Supporting Evidence for the Selection Channel

In the theory section of the main text, we hypothesize that during downturns more individuals want to enter academia and, due to a fixed number of open spaces at entry to the PhD, only a favorable selection with superior ability is admitted. Unfortunately, however, we see ourselves unable to provide direct evidence for the selection mechanism at work. This is for the following reason:

In order to gather evidence, we were looking for data that provides observable ex ante characteristics of the students admitted to the PhD programs which we could then relate to the state of the business cycle. We obtained Graduate Record Examination (GRE) scores for a non-US PhD program that is comparable to a tier two school. The GRE consists of three sections: quantitative, verbal and analytical writing. In all universities, GRE scores are considered an obligatory part of the application documents and it is generally agreed that it is almost exclusively the quantitative section that matters for admission. For this reason, our GRE scores proved to be uninformative. We found that, independently of the state of the business cycle, virtually everyone accepted to the PhD as well as most applicants had the highest possible mark (800 points) in the quantitative section.

In general, we are very skeptical that easily observable ex ante characteristics, such as GRE data or undergraduate GPAs, of applicants or entrants would be informative about the selection into the programs because many successful and unsuccessful applicants do not differ in these dimensions. The truly informative quality differences of applicants and entrants are most likely to be more subtly hidden in "softer" information such as reference letters, research assistantships and types of courses taken during the undergraduate degree. This kind of information is very hard to obtain and to process in an objective way.

Although we are unable to present direct evidence for our hypothesized channel, Kelly Bedard and Douglas Herman published a study in the Economics of Education Review (2008) that documents supporting evidence for our main selection channel. They use data on recently graduated science and engineering Bachelor and Master students from 1990 to 2000 which is provided in the 1993 to 2001 National Survey of Recent College Graduates (NSRCG). Exploiting the variation in state-level unemployment rates, Bedard and Herman find that male PhD enrollment is countercyclical and the counter-cyclicality is driven by students with a high GPA in the hard sciences.[39] They state that the unemployment rate responses for this group are fairly precisely estimated and that their estimates imply a one-percentage point increase in the unemployment rate increases "high GPA" male Ph.D. enrollment by 0.356 percentage points.

In another paper, Fougere and Pouget (2003) find that the applications per spaces ratio in the French public sector rises strongly in economically hard times. Unfortunately they do not provide a quality measure of French public sector workers.

[39] They look at entry into all PhD programs in terms of quality and subject and not our only the top 30 economics programs. Therefore, quantity constraints at entry to the PhD should matter much less and it is not surprising that they not only find the expected quality differences of entrants with respect to the business cycle, but also quantity differences. Moreover, it is also not surprising that GPAs matter (more strongly) for engineering and science majors and for a broader range of graduate schools than just the top 30 departments.

F Robustness Checks

In this section which is not intended for publication we estimate different variants of our main empirical model in order to scrutinize the robustness of the results.

We restate our main findings in table 15: A recession at application leads to a more productive selection of academics (column 3). The propensity to become an academic is decreasing with unemployment change at application and increasing with unemployment change at graduation (column 2). Cohorts graduating in a recession are publishing more (column 1).

[Insert table 15 about here]

In the following we consider NBER recession indicators and GDP growth as alternative measures for the business cycle, time trends as control variables instead of decade dummies, and different assumed durations for the PhD. In a subsample analysis we remove "superstar" economists who are exceptionally prolific to show that the results are not entirely driven by outliers.

F.1 Alternative Measures for the Business Cycle and Controls for the Time Trend

[Insert Table 16, Table 17, Table 18, Table 19 and Table 20 about here.

Table 16 reports the correlations between potential measures of the business cycle over our sample period including the dates at application and at graduation from the PhD. The NBER recession indicators are most strongly related to the change in unemployment and GDP growth. We thus repeat our main specification with NBER recession indicators and GDP growth as a measure for the business cycle in Tables 17 and 19.[40] The results for the recession indicators are qualitatively the same as in our main regressions and they are significant for three out of the four predictions of the model. This is reassuring. Note that an increase in GDP indicates a boom and a decrease a recession. Therefore, the sign of the coefficients are reversed. The results

[40]The growth of GDP might well proxy for a (potential) economist's earnings potential in outside employment with performance pay such as the financial sector.

on productivity hold up very well: the effect of unemployment change at application as well as at graduation are not only in the direction that the theory predicts but also significant. The direction of the coefficients is also correct in the regressions with alternative interpretations of being an academic (Tables 18 and 20).

[Insert Table 21 and Table 22 about here]

Another concern might be that our graduation decade dummies inadequately control for the general trends in academia over time. In Table 21 we therefore report the main regression with university dummies and a linear and quadratic time trend instead. The results of the main section on productivity are largely robust. Only the productivity of academics at graduation is not significant anymore, but theory made no prediction for the signs of this parameter in the first place. The results on the propensity to become an academic have the right sign and at application they are significant at the 10% level. The picture stays the same if we use different measures for being an academic in Table 22.

F.2 Alternative Measures for Being an Academic

In the main text, we report three different measures which might indicate that an individual is an academic: Our standard "academic" measure equals one if he is a faculty member or a member of the American Economic Association after graduation from the PhD. The second measure is one if the PhD student becomes a faculty member at a US business, economics or finance department and the third one shows if the student is able to publish in one of our ranked journals after graduation. In the main text, due to conciseness, we left out the robustness of our productivity regressions of academics with regard to the last two measures. In Table 23, we report this robustness check for completeness. All coefficients have the correct sign and they are significant at conventional levels (except the unemployment change at graduation for the faculty measure).

[Insert Table 23 about here]

F.3 Alternative Duration of the PhD

We explain in our data section that we impute the application date by subtracting six years from the graduation date. The rationale for the difference of 6 years is explained in section B.5 in the appendix. In Tables 24 and 25, we change the duration of the PhD to 5 and 7 years, respectively.

[Insert Table 24 and Table 25 about here]

The effect at graduation stays the same, of course, but the effect at application all but vanishes. We interpret this as a support for our argument of an estimated difference of 6 years between application and graduation.

F.4 Exclusion of Superstar-Economists

Finally, we want to make sure that our results are not driven by the exceptional performance of very few superstar-economists whose extraordinary talent would have made them academics independently of any state of the business cycle.

[Insert Figure 11 about here]

First, consider in Figure 11 the distribution of individuals' publication success as a histogram and over time. The modus and the median of the distribution of publications is zero while the mean is 31.49. Only 80 economists achieve more than 500 publication points with Nobel laureate Joseph Stiglitz scoring a stunning maximum of 1738 points. In Table 26, we report the results of our main regressions if we remove the 80 economists who publish more than 500 points. We see that our main results are not driven by these "outliers".

[Insert Table 26 about here]

Tables

	Unem Ch App	Unem Ch Grad	GDP Ch App	GDP Change Grad
Unem Ch App	1.000			
Unem Ch Grad	-0.151	1.000		
	(0.271)			
GDP Ch App	-0.786***	0.158	1.000	
	(0.000)	(0.251)		
GDP Change Grad	0.130	-0.862***	-0.114	1.000
	(0.345)	(0.000)	(0.405)	
Observations	57			

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Correlation of unemployment change and GDP change at application and at graduation (university-year level)

	Unem Ch Grad	Unem Ch App	# Graduates (AEA)	# Graduates (NSF)	# Entrants (NSF)	Attrition (NSF)
Unem Ch Grad	1.000					
Unem Ch App	-0.131	1.000				
	(0.419)					
# Graduates (AEA)	0.019	-0.168	1.000			
	(0.906)	(0.300)				
# Graduates (NSF)	0.149	-0.077	0.351*	1.000		
	(0.440)	(0.692)	(0.062)			
# Entrants (NSF)	-0.075	0.081	0.141	-0.018	1.000	
	(0.698)	(0.675)	(0.466)	(0.910)		
Attrition (NSF)	0.205	0.395	-0.395	-0.325	0.249	1.000
	(0.430)	(0.117)	(0.116)	(0.122)	(0.241)	
Observations	53					

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Correlation of unemployment change with attrition, the number of entrants and graduates (year level)

	Productivity	Academic	Productivity
Unempl Change (Application)	1.540**	-0.891	3.274***
	(0.661)	(0.576)	(0.945)
Unempl Change (Graduation)	2.312***	1.354**	2.738**
	(0.645)	(0.607)	(1.199)
Subsample	All	All	Academic
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Main regression results

	Rec Indic	Unem Level	Unem Change	GDP Level	GDP Growth
Rec Indic	1.000				
Unem Level	0.375**	1.000			
	(0.010)				
Unem Change	0.619***	0.340**	1.000		
	(0.000)	(0.021)			
GDP Level	-0.109	0.512***	-0.085	1.000	
	(0.470)	(0.000)	(0.573)		
GDP Growth	-0.393***	-0.330**	-0.869***	-0.133	1.000
	(0.007)	(0.025)	(0.000)	(0.377)	
Observations	46				

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Correlation of unemployment change and GDP change at application and at graduation (university-year level)

	Productivity	Academic	Productivity
Recession Indicators (Application)	2.163	-3.240**	5.378*
	(2.108)	(1.548)	(2.934)
Recession Indicators (Graduation)	4.563**	2.149	5.094
	(2.140)	(1.289)	(3.568)
Subsample	All	All	Academic
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Alternative business cycle measures: Recession Indicators

	Academic	Faculty	Publish	Academic
Recession Indicators (Application)	-3.240**	-1.415	-1.791	-5.734***
	(1.548)	(1.061)	(1.198)	(1.727)
Recession Indicators (Graduation)	2.149	1.839**	1.138	3.946**
	(1.289)	(0.760)	(0.836)	(1.675)
Subsample	All	All	All	Tier 1
Univ-Decade Dummies	Yes	Yes	Yes	Yes
Observations	1068	1068	1068	234

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Alternative business cycle measures: Recession Indicators

	Productivity	Academic	Productivity
GDP Change (Application)	-0.658**	0.472*	-1.456***
	(0.286)	(0.245)	(0.421)
GDP Change (Graduation)	-0.705**	-0.407	-0.739
	(0.326)	(0.273)	(0.557)
Subsample	All	All	Academic
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Alternative business cycle measures: GDP change

	Academic	Faculty	Publish	Academic
GDP Change (Application)	0.472*	0.248	0.448**	0.750**
	(0.245)	(0.194)	(0.189)	(0.287)
GDP Change (Graduation)	-0.407	-0.047	0.051	-1.247***
	(0.273)	(0.193)	(0.229)	(0.361)
Subsample	All	All	All	Tier 1
Univ-Decade Dummies	Yes	Yes	Yes	Yes
Observations	1068	1068	1068	234

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Alternative business cycle measures: GDP change

	Productivity	Academic	Productivity
Unempl Change (Application)	1.873**	-0.942*	3.555***
	(0.723)	(0.534)	(1.013)
Unempl Change (Graduation)	1.551**	0.635	1.736
	(0.649)	(0.582)	(1.169)
Subsample	All	All	Academic
Time trend	Yes	Yes	Yes
Observations	1068	1068	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Alternative controls: linear and quadratic time trend

	Academic	Faculty	Publish	Academic
Unempl Change (Application)	-0.942*	-0.083	-0.501	-1.214*
	(0.534)	(0.393)	(0.318)	(0.637)
Unempl Change (Graduation)	0.635	0.025	0.044	1.493
	(0.582)	(0.418)	(0.460)	(0.905)
Subsample	All	All	All	Tier 1
Time trend	Yes	Yes	Yes	Yes
Observations	1068	1068	1047	232

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Alternative controls: linear and quadratic time trend

	Productivity	Productivity	Productivity
Unempl Change (Application)	3.274***	6.837***	5.630***
	(0.945)	(2.471)	(1.291)
Unempl Change (Graduation)	2.738**	2.353	4.352***
	(1.199)	(1.868)	(1.094)
Subsample	Academic	Faculty	Publish
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1047	906	974

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Alternative measure for being academic: Productivity

	Productivity	Academic	Productivity
Unempl Change (Application)	-0.648	-0.502	-0.609
	(0.659)	(0.584)	(1.035)
Unempl Change (Graduation)	2.220***	1.455**	2.502*
	(0.738)	(0.603)	(1.359)
Subsample	All	All	All
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Alternative duration of PhD (5 Years)

	Productivity	Academic	Productivity
Unempl Change (Application)	-0.325	-0.853	-0.420
	(0.730)	(0.528)	(1.275)
Unempl Change (Graduation)	2.200***	1.467**	2.502*
	(0.661)	(0.599)	(1.287)
Subsample	All	All	Academic
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25: Alternative duration of PhD (7 Years)

	Productivity	Academic	Productivity
Unempl Change (Application)	1.048	-0.008	2.358**
	(0.628)	(0.006)	(0.875)
Unempl Change (Graduation)	1.508**	0.010	1.835*
	(0.559)	(0.006)	(1.010)
Subsample	w/o Superstars	w/o Superstars	Academic w/o superstars
Univ-Decade Dummies	Yes	Yes	Yes
Observations	1068	1068	1047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Main regression results "ex superstars"

Figures

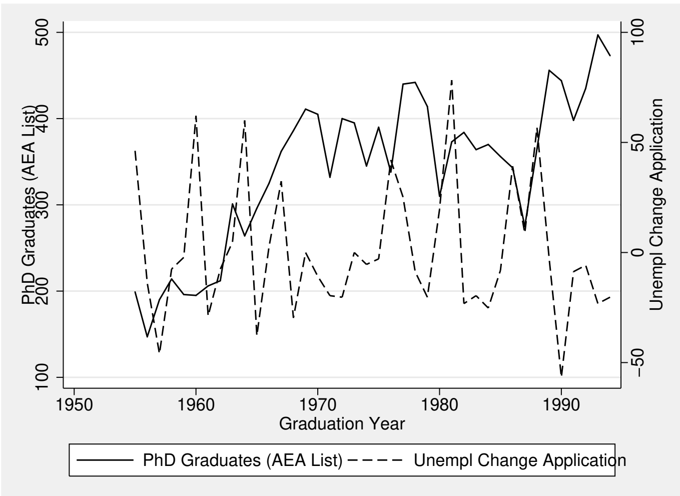


Figure 10: Number of graduates and unemployment change at application

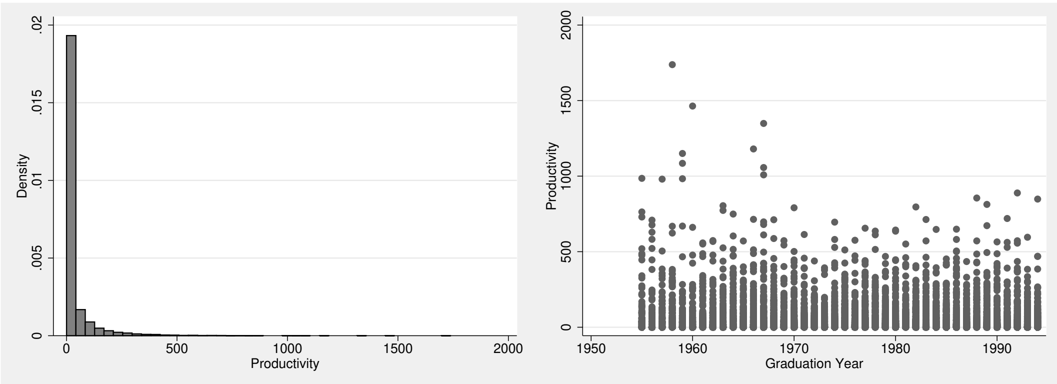


Figure 11: The publication distribution